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Youth Crime and Delinquency In And Out Of School

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Abstract

This paper combines ten years of idiosyncratic variation in school closure dates for all secondary schools in England with administrative records of educational and criminal trajectories linked at the individual level to study the impact of the school schedule on the dynamics of youth crime. When school is not in session, students commit more property offences, more serious violent offences and fewer minor violent offences. Thefts, robberies and violent assaults drive these effects. This is novel evidence of strong incapacitation effects from the protective factor of schooling which affects not only the incidence of violence, but also its severity.

JEL keywords: Crime; School Attendance; Exclusion.
JEL classifications: I2, K14, K42, H44.

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1. Introduction

Compulsory schooling is frequently viewed as a means of delivering societal benefits. One feature is that, because the economic and social costs of crime are high, the crime reduction that results from juveniles being in school, kept busy in a supervised environment and thus off the streets, generates significant social benefits. A link between crime and school attendance has been documented for most crime types and in a variety of settings, including the US (Jacob and Lefgren, 2003; Lochner and Moretti, 2004; Luallen, 2006; Anderson, 2014; Bell et al, 2016 and 2022; Cook and Kang, 2016; Cano-Urbina and Lochner, 2019), England and Wales (Machin et al, 2011) and Sweden (Hjalmarsson et al, 2015). The consensus is a property crime-reducing effect of school attendance (Machin and Sandi, 2025).

Currently less well-understood are the means by which in-school behaviour responds to legislative change mandating compulsory school attendance. While one of the main rationales behind compulsory schooling is to improve the human capital and labour market prospects of potential early dropouts, the primary experience of compulsory education for disruptive students is attending school surrounded by better-performing peers. Compulsory schooling laws often rest on a somewhat paternalistic view that unruly juveniles are actually better off staying on in class rather than leaving school at a younger age (Messacar and Oreopoulos, 2012).

However, when this occurs, relatively little is known about their behaviour in school. If juveniles are kept in school and disengaged from learning, delinquency in school may increase. Fellow students may suffer significant costs including increased bullying, gang activity, threats or a reduced perception of safety in school, which may affect their wellbeing and learning process. Disruptive peers may hinder school performance (Robertson and Symons, 2003; Figlio, 2007; Carrell and Hoekstra, 2010; Sarzosa, 2024) and decrease future earnings (Carrell et al, 2018), while raising the risk of drug use (Gaviria and Raphael, 2001; Kawaguchi, 2004; Lundborg, 2006; Powell et al, 2005), cheating (Carrell et al, 2008), indiscipline in the classroom (Carrell and Hoekstra, 2010), depression (Wang et al, 2011), anxiety (Kowalski and Limber, 2013) and suicidal thoughts and behaviours (Holt et al, 2015). These negative effects of bullying continue also after the abuse ends and they correlate with a broad set of physical, mental and economic difficulties in adulthood (Takizawa et al, 2014; Wolke et al, 2013; Wolke and Lereya, 2015). Among US high school students, over 20% reported being bullied in person at school and 16% reported being cyberbullied in 2018 (Basile et al, 2020). Thus, school bullying is widespread and causes substantial harm to the students involved.

This paper studies the causal impact of compulsory schooling on the day-to-day possibility, desire and actual act to commit crime by combining idiosyncratic variation in school closure dates for all secondary schools in England with administrative records of educational and criminal trajectories linked at the individual level. Administrative records of all school closure dates were collected for all state-maintained secondary schools in England from the 1st August 2010 to the 31st December 2019. The school calendar data contain detailed information on when school is in session and the reason for school closures (e.g., winter, spring or summer school break, national holiday, or teacher training). Secondary schools in England set their half-term breaks and teacher training dates independently, generating extensive variation in the timing of school closures across schools and over time.

For all students in state-maintained secondary schools in England, administrative records of their complete schooling trajectories from the Department for Education were linked at the individual level with administrative records of their complete criminal trajectories from the Ministry of Justice. These very rich microdata allow us to overcome the quite severe previous data constraints in existing work on school incapacitation, resulting from use either of self-reported surveys that do not identify perpetrators or of locality-level aggregated data. The granularity of our data for the universe of students in England allows us to rectify this and offer novel, strong insights on school attendance and youth crime.[1] Our data enable us to follow pupils through from school discipline sanctions on to observing the severity of the crimes committed on these dates and their repercussions in the criminal justice system.

The panel dataset follows pupils through their entire school history in all state-maintained secondary schools in England with daily frequency from 2010 to 2019, and links to their criminal histories at the individual-level whilst in school and subsequently once they have left. The analysis starts by showing descriptively the trends in property and violent crime on "normal" schooldays, on weekdays when school is not in session, during weekends, and during the autumn, spring and summer breaks. The trends that emerge across the school calendar appear similar to those in school bullying and cyberbullying in the US prior to the Covid-19 pandemic (Bacher-Hicks et al, 2022).

The research design implemented in this paper isolates the causal impact on youth crime of idiosyncratic weekdays when school is not in session from the impact of weekends and other school breaks, which may not be comparable to "normal" weekdays when school is in session. The severity of crime is defined using the distinction in the British criminal justice system between indictable offences, which constitute the most serious offences, summary offences, which constitute minor offences, and offences that are triable either way as their severity depends on the specific case. By including a series of fixed effects for date and school, our analysis shows that property crime and indictable violence increase while summary violence decreases during weekdays when school is not in session. Although our focus is on youth aged 11-15, i.e., under-age, these offences can result in convictions in court, thus potentially having lasting consequences for the criminal trajectories of the juveniles involved. These conclusions are robust to the use of alternative estimation techniques.

[1] Throughout the paper, "school attendance" refers to the timing of school openings and not the actual school attendance decision by the students that is potentially endogenous in the crime equation.

Increased property crime is driven by increased thefts while the increased indictable violence is driven by increased robberies, which are typically committed outside school.[2] Since these results appear also when only court convictions are considered and they are unaffected by the number of schools in the locality that close on the same weekday, they do not seem to reflect differential crime clearance rates by the police when just a few students are off from school. Moreover, neither property or violent crime nor permanent exclusions by school directors for property or violent misconduct decrease in the days immediately before or after the weekday off. Thus, students do not seem to "substitute" delinquent acts from one day to another. In contrast, a genuine incapacitation effect of school on crime appears to be the prime factor governing the dynamics of thefts and robberies.

The reduced incidence of summary violent offences, i.e., minor acts of violence, is mostly driven by reduced assaults against the person, which are typically committed in proximity to other students (although cyberbullying may constitute an exception). Neither violent crime nor permanent exclusions by school directors for violent misconduct increase in the days immediately before or after the weekday off. Thus, students do not seem to hold grudges and "substitute" violence between one day and another. Unlike our conclusion for property crime, the reduction in summary violence during school closures is mitigated by the number of other schools in the locality that are not in session on the same day. This is coherent with a concentration effect of school on minor acts of violence, as it suggests that minor acts of violence increase when all students are forced in the same place and the greatest reduction in minor acts of violence appears when some students have to attend school and others do not.

These findings have four important implications. First, by showing that school attendance reduces the incidence of indictable violence and it increases the incidence of summary violence, they provide at least strongly suggestive evidence that schools may prevent not so much the *incidence* but rather the most serious types of physical violence. While the existing incapacitation literature shows that the incidence of violence increases when school is in session (Jacob and Lefgren, 2003; Anderson, 2014; Bacher-Hicks et al, 2022; Machin and Sandi, forthcoming), no study to date has examined the impact of schooling on the *severity* of physical violence. We provide novel evidence that the protective factor of schooling may act by reducing the *severity* of physical violence. This is important because, compared with victims of summary violence, victims of indictable violence often suffer more severe physical injuries and require greater access to legal and psychological support (Bureau of Justice Statistics, 2022), while also facing higher levels of psychological distress, post-traumatic stress disorder and medical expenses (Langton and Planty, 2024).

Second, by exploiting otherwise innocuous weekdays off from school, this study shows that in-person interactions at school are important drivers of minor acts of violence among students. Based on

[2] For evidence on robbery location figures, see, e.g., [FBI — Robbery](#).

our analysis, schools in the same locality should set their closure dates on different weekdays, as the contemporaneous school absence of students from different schools may result in increased assaults.

Third, by showing mixed evidence of school attendance on different crime categories, these results point towards one plausible mechanism behind COVID-19's mixed impacts on mental health. Brodeur et al (2021), for instance, show that COVID-19 reduced stress and suicidal thoughts. Bacher-Hicks et al (2022) show that online searches for both school bullying and cyberbullying in the US reduced by roughly 30–35% during the Covid-19 pandemic, suggesting that reduced bullying may have been an unexpected benefit of reduced in-person interaction. The findings of reduced minor acts of violence when school is not in session are consistent with the notion that reduced in-person interaction can have mixed effects on individual wellbeing.

Fourth, from a policy perspective, this study highlights the need to supplement youth justice policies and compulsory school policies with services that help keep students safe and engaged in learning and prevent the potential increase in minor acts of violence on school-days documented here. This intuition can also be extended to other settings (e.g., parks, recreation centres, youth centres, sport activities) to appreciate their potential unintended effects. To the extent that these settings attract several youths to the same place, they will increase the number of interactions between youths, and thus they might increase the potential number of violent conflicts.

2. Data

DfE-MoJ data linkage

The empirical analysis uses individual-level administrative data matching education and criminal records from the Department for Education (DfE) and the Ministry of Justice (MoJ) from the 1st August 2010 to the 31st December 2019 for the entire population of students in state-maintained secondary schools in England. The DfE data extract contains administrative records of pupil-level achievement at various stages of the school trajectory and pupil characteristics, such as gender, free school meal eligibility, ethnicity, native language and school of enrolment at all stages of education.

The criminal records of juveniles in England are extracted from the MoJ's Police National Computer (PNC). The PNC stores criminal records' information across England and Wales. It is maintained by the UK Home Office and it holds approximately 13 million person records with precise information on all the criminal offences for which an individual has been cautioned or convicted, as well as detailed information on the nature and date of the offence and on the age of the offender.[3] This information is used to define our outcome of interest, namely the risk and count of offences committed by an individual on a given date. Data on the nature of the offence allow us to distinguish indictable

[3] Offences that are not recorded in the data include, e.g., TV evasion.

offences, i.e., more serious offences, from summary offences, for which the sentence cannot exceed six months of imprisonment. While the British justice system unambiguously treats some offences as summary, e.g., traveling on public transport without paying the fare, other crimes, such as theft, are triable either way and the distinction between indictable and summary offences depends on the specific case.

Criminal records are also grouped into property crime, which includes theft, criminal damage and arson, burglary; and violent crime, which includes violence against the person, sexual offence and robbery. Total crime is defined as the sum of property and violent crime.[4] Finally, our data allow us to follow individuals from the date of the offence through the criminal justice system, as they include information on the recorded result of the court hearing. The data do not allow us to compare "guilty" vs "non-guilty" individuals and the lack of a conviction should not be interpreted as "non-guilty" (e.g., a caution is not a court conviction but it is an official warning from the police that is usually given for a minor crime, where the offender has admitted to the offence and has agreed to be cautioned). However, this information is used to restrict our analysis to court convictions and check robustness of our findings.

School term and holiday dates

The DfE-MoJ data linkage was combined with data on the school term and holiday dates for every state-maintained secondary school in England from the 1st August 2010 to the end of 2019. In England, the school year is composed of three terms, i.e., the autumn term from September to December, the spring term from January to the Easter break (typically between March and April) and the summer term from the Easter break to mid-July, when the school year terminates. Within terms, schools have the power to set independently their half-term dates, which are school breaks ranging from five to ten days. While the school terms start and terminate at the same time for all schools (with few exceptions), the timing of half-terms are set independently and they display substantial variation across schools. Our analysis exploits this variation, as it allows us to compare the behaviour of youths in different schools when their respective schools are not in session.

An additional source of plausibly exogenous variation in the timing of compulsory school attendance is generated by IN-SErvice-Teacher-training (INSET) dates. INSET dates can be either used by the schools to train the school personnel on a specific matter or to provide teachers with time to focus on administrative or professional tasks. In a school year, there are typically five INSET dates and each school can decide independently when they are held and whether they will affect the whole school or just a few classes. INSET dates are posted on the school website and they are communicated to parents and educators well in advance. The variation in the timing of compulsory school attendance induced by the INSET dates is also exploited in our analysis.

[4] Other crime categories, e.g., drugs, are not studied here.

Information on the entire school calendar, including the start- and end-dates of half-terms and INSET dates, was scraped from the school websites and schools were contacted directly whenever this information could not be obtained from their websites. This resulted in the construction of a dataset that covers nearly the entire universe of state-maintained secondary schools in England and that only excludes private schools. This dataset was combined with the DfE-MoJ dataset and the count of offences by category was calculated for all students in each school and each date. Table 1 shows the resulting panel dataset on delinquent behaviour at the school level for all state-maintained secondary schools in England with daily frequency from 2010-19.[5] In Table 1 as in the remainder of our exhibits, all our displayed school*day averages and estimated coefficients are weighted by the count of students enrolled each school year in each school and they are multiplied by 1000 for easier readability.

Descriptive patterns

Our sample includes 3,264 secondary schools and 3,440 days (i.e., from the 1st August 2010 to the 31st December 2019), resulting in a total of 11,228,160 school*day observations. Of these, Table 1 shows that 5,885,406 observations are on "normal" schooldays (52.42%), while 509,831 observations are on weekdays when school is not in session either because of half-term breaks or because of INSET dates: these are the dates that generate our identifying variation and they constitute approximately 4.54% of our sample. Of the remainder, 3,208,512 observations are on weekends (28.57%), 332,446 observations are during the winter breaks (2.96%), 314,381 observations are in the spring breaks (2.8%) and 977,584 observations are in the summer break (8.7%).[6]

Table 1 shows descriptively that total crime, defined as the sum of property and violence, significantly increases on weekdays when school is not in session and during spring breaks, while it reduces during weekends, winter breaks and summer breaks. Property crime significantly increases on weekdays when school is not in session, during weekends and spring breaks, while it reduces in winter breaks. In contrast, violent crime decreases both during weekends and in winter and summer breaks, while the evidence appears somewhat more mixed on weekdays when school is not in session and spring breaks. The violence reduction during summer breaks is likely explained by the fact that a six-week break is common in England and students may travel, thus changing the scope and venue of crime.

3. Empirical strategy

The main challenge in the estimation of the day-to-day impact of school attendance on crime is that schooldays are not randomly distributed across the year. Crime may be systematically more or less common on days when school is not in session for several reasons. For instance, the days from mid-July

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[5] Appendix Table A.1 shows descriptive statistics for property and violent crime separately by indictable (or triable either way) and summary offences.

[6] The count of different dates found in each group needs not add up to the total of 3,440 dates in our sample precisely because each school sets their calendar dates independently and, thus, not all schools close on all the dates when other schools close.

to the end of August are typically not schooldays in England: as criminality rises with temperature (Jacob et al, 2007), using the summer break to test how property crime changes when school is not in session would bias our estimates upwards. Similarly, weekends are not schooldays either. However, to the extent that more people are in the street and at social events on weekends, the potential returns from property crime might be higher, which in turn would also bias our estimates upwards.

We address these endogeneity concerns by focusing on the variation generated by the half-term dates and IN-SErvice Teacher (INSET) dates. A similar approach is used in Jacob and Lefgren (2003). Like in the US, INSET dates in England are weekdays where students do not attend school and that teachers use for professional development, teacher conventions, planning, or parent-teacher conferences. Similar to Jacob and Lefgren (2003), we argue that these days are very unlikely to correlate with any other systematic factors influencing the level of youth criminality. Our data include multiple school years and variation appears both within and between schools and over time in the dates of half-term breaks and INSET dates. Our analysis includes a set of date fixed effects, e.g., 1st September 2010 fixed effects, and school fixed effects, to account for anything specific to a particular date or a particular school that may correlate with youth crime. For secondary school *i* on day *t*, the equation of interest is:

$$Y_{it} = a_i + a_t + \beta_1 * OFF_{it} + \epsilon_{it}, \tag{1}$$

where Y_i is either the risk (0/1) or the count of criminal offences committed by the students enrolled in school *i* on day *t*, a_i is a set of school fixed effects and a_t is a set of date fixed effects. OFF_{it} is a binary variable that takes value 1 if school *i* is not in session on a weekday *t* during the school year and value 0 otherwise. Therefore, OFF_{it} takes value 0 during weekends and during the winter break, spring break and summer break. The coefficient of interest is β_1, as it captures the effect of school closures on crime during weekdays when school is normally in session. Standard errors are clustered at the school level and ϵ_i is the error term. For binary outcomes, equation (1) is estimated by OLS techniques (i.e., a linear probability model) and probit techniques. When the outcome variable is the count of crime, Poisson Pseudo-Maximum Likelihood (PPML) estimates are also shown since crime is a rare event and the count dependent variable has many zeros. The Appendix also shows robustness estimates with the count of crimes committed by the students at school *i* on weekday *t* deflated by the count of students in school *i*.

4. Results

Main results

Table 2 shows the main OLS estimates of the study. Panel A shows estimates of the impact of school closure on the risk (0/1) of total crime in columns (1)-(3), the risk (0/1) of a conviction in court for total crime in columns (4)-(5), the count of total crime in columns (6)-(8) and the count of convictions in court for total crime in columns (9)-(10). Panels B, C, D, E, F and G do likewise for the various crime categories included in our definition of total crime. In particular, Panel B focuses on property crime, Panels C and D break it down between indictable (or triable either way) and summary property crime, Panel E focuses on violent crime and Panels F and G break it down between indictable and summary violent crime. All estimates include fixed effects for date, winter break, spring break and summer break. While columns (1) and (5) omit school fixed effects, they are included in the estimation in all other columns, with columns (3), (5), (8) and (10) additionally controlling for the count of schools closed on a given date in the Local Education Authority (LEA).

Panel A shows that the count of criminal offences increases by roughly 9%-10% in weekdays when school is not in session.[7] This conclusion is robust to the use of alternative sets of fixed effects and to restricting the focus on court convictions. A smaller, statistically insignificant increase appears in the risk of committing crime, suggesting that this effect is not driven by marginal offenders. Panel B shows that both the risk and the count of property crimes and convictions for property crimes increase when school is not in session, as an 11.2%-12.6% increase in the risk of property crime and a 15%-25.7% increase in the count of property crime are estimated. Panels C and D split property crime between indictable (or triable either way) and summary property crime, showing that the former drive the results in Panel B. Indictable (or triable either way) property crimes include theft, criminal damage and arson and burglary, and in most cases the magnitudes of these effects are slightly larger than those in Panel B. Summary property crimes include, e.g., traveling on public transport without paying the correct fare, failing to show ticket, interference with motor vehicle/trailer, taking or riding a pedal cycle without consent, etc. The lack of significance for these petty crimes might reflect a genuine null effect or the fact that many of these go unnoticed, resulting in measurement error in our estimates.

One may wonder whether these results reflect the improved crime clearance rate by the police when just a few students are off from school and in the street, rather than a genuine increase in criminal activity. With most juveniles in school and just a few students in the street, it might be easier for the police to clear crime on these particular dates. However, the consistency in the results that focus on court convictions should mitigate the concern that our estimates reflect the differential crime clearance rate on these dates. Moreover, the count of schools closed on a weekday either because of half-term breaks or because of INSET dates was calculated for each date and each LEA, i.e., in each locality. If our results reflected the greater crime clearance rate, our effects should be mitigated or even cancelled out by the contemporaneous school closures of multiple schools in the same locality. As columns (3), (5), (8) and (10) in Panels A-D show, the interaction between our treatment status of interest and the count of schools closed in the locality is never significant and numerically very small, indicating that our conclusions are

[7] In Table 2, % effects are derived dividing the estimated coefficient by the mean of the outcome variable on school-days.

not affected by the simultaneous school closures of multiple schools in the same locality and in turn suggesting that our results do not reflect the increased crime clearance rate by the police when just a few students are off from school.

Panels E, F and G focus on violent crime. The estimates indicate that indictable and summary violence follow opposite dynamics when school is not in session. On these dates, the risk of indictable violence increases by 9.2%-10.1%, the risk of a court conviction for indictable violence increases by 20.4%-24.9%, the count of indictable violence increases by 15.1%-17.5% and the count of court convictions for indictable violence increase by 20.5%-23.7%. In contrast, when school is not in session, the risk of summary violence reduces by 14.8%-17.8%, the risk of a court conviction for summary violence reduces by 12.2%-18.5%, the count of summary violence reduces by 13.6%-18.5% and the count of court convictions for summary violence reduce by 9%-16.4%.

These results confirm that violence may increase when school is in session, but they also point towards a novel means by which school attendance may exert a protective factor on adolescents, namely by preventing the escalation of violence and reducing its severity. Moreover, unlike all other crime categories, the estimated significance in the interaction between our treatment of interest and the count of schools closed in the locality on a specific date indicates that the reduction in summary violence is partially offset when other schools in the same locality are closed on the same day. This finding appears consistent with the concentration effect of school on violence, as it suggests that separating juveniles also in the timing of their days off from school is likely to exert the greatest violence-reducing effect.[8]

Crime displacement and school exclusions

School attendance could merely alter the place or timing of youth delinquency, whilst not impacting its overall level. Indeed, as delinquency in school is not always reported to the police, the increase in property crime in Table 2 might reflect the greater likelihood of delinquency outside school to get reported. Also, when school is not in session, increased property crime may compensate the reduced property misconduct in school. Moreover, youth who plan to steal something from a local shop may think it sensible to do it on a day off from school. Similarly, juveniles planning to seek revenge on their rivals could choose to do it on a school day because the other juveniles will be nearby and/or because they may want others to witness the revenge. In these cases, our estimates may not reflect genuine changes in the amount of delinquency in aggregate over the longer run.

Our empirical analysis adopts two strategies to address these concerns. First, it examines permanent exclusions from school for property misconduct and violent misconduct. In England,

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[8] Appendix Table A.2 displays our probit estimates of the impact of school closures on the risk of crime. Appendix Table A.3 displays our Poisson Pseudo-Maximum Likelihood (PPML) estimates of the impact of school closures on the count of crimes. Appendix Tables A.4 and A.5 also show OLS and PPML estimates when the count of crimes committed by the students enrolled in school i are deflated by the count of students enrolled in school i. Appendix Tables A.2, A.3, A.4 and A.5 are organised similarly to Table 2 and estimates appear consistent with those in Table 2.

permanent exclusions are equivalent to school expulsions in the US and therefore are the most directly comparable disciplinary actions a school director can take in response to bad behaviour. Second, it examines the level of youth crime and permanent exclusions on the days just before and just after the weekdays off from school. If juveniles simply saved all of their grudges, vendettas, and other violent acts for days when school was in session, one might expect there to be unusually high levels of crime on the days just before or after school was not in session to compensate for the unusually low levels of violent crime on non-school days. Since not all violence may result in a criminal offence, administrative records from the Department for Education on permanent exclusions from school constitute a valuable complement to the crime records of the Ministry of Justice.

Table 3 shows estimates of the impact of school closures on the count of permanent exclusions and crimes. To be precise, Panel A focuses on total permanent exclusions and total crimes, while Panels B and C break down the total into property misconduct and property crime (Panel B) and violent misconduct and violent crime (Panel C). Columns (1)-(2) show OLS estimates for permanent exclusions, while columns (3)-(5) and columns (6)-(8) show, respectively, OLS and PPML estimates for the combined permanent exclusions and criminal offences by category. In England, pupils can be excluded from school also for misconduct outside the school premises and on dates when school is not in session. Perhaps not surprisingly, columns (1)-(2) show that permanent exclusions reduce almost entirely by 97% when school is not in session, with permanent exclusions for property misconduct dropping by 68%-69% and exclusions for violent misconduct dropping by 98.8%-98.9%. When crime offences and permanent exclusions are combined, both OLS and PPML estimates in Panel A appear statistically insignificant, reflecting the contrasting effects of compulsory school attendance on different types of crime. Panel B shows that, when property offences and property exclusions are combined, the results look like a replication of those in Table 2. Thus, the evidence in Table 3 provides no empirical support to the concern that the increase in property crime may merely compensate reduced property misconduct when school is not in session. Panel C also reiterates the conclusion that violence reduces when school is not in session by showing that violent exclusions are affected in the same direction as summary violent crimes.

Chart 1 uses both crime records and permanent exclusions in school to test whether school attendance merely alters the timing of youth delinquency. Panel A focuses on total crime and total exclusions, Panel B focuses on property crime and property exclusions and Panel C focuses on violent crime and violent exclusions. The left-hand side charts display results for criminal records while the right-hand side charts combine criminal and exclusion records. Specifications (1) and (2) show OLS estimates with and without school fixed effects and specifications (3) and (4) do likewise for PPML estimates. Both the individual and joint tests of significance of the "Pre" and "Post" coefficients are displayed in each chart. In all cases, Chart 1 shows that crime and exclusion records did not vary significantly in the days just before or just after the school closure dates, suggesting that the increase in property crime and indictable violence and the decrease in summary violence on the school closure dates reflect genuine changes in the amount of delinquency in aggregate over the longer run.

Different crime categories

What crimes do juveniles actually commit in and outside school? Table 4 shows estimates where the counts of property and violent crime are broken down into finer categories. Columns (1)-(3) display OLS estimates while columns (4)-(6) display PPML estimates. Panels A, B, and C focus on various categories of property offences. They show that the increased incidence of property crime when school is not in session is mainly driven by increased thefts, which are typically committed outside school. Thus, a genuine incapacitation effect of school on crime appears to be the prime factor governing the dynamics of these property crimes.

Panels D, E and F in Table 4 turn the attention to violence. Panel D shows that the incidence of robberies significantly increases when school is not in session. Although robbery is a violent offence, it is an indictable offence that is typically committed in the street. Therefore, an incapacitation effect of school appears also in this case to be the prime driver. Panels E and F show that, when school is not in session, the incidence of violence against the person significantly reduces, while a non-significant reduction in sexual violence also appears. Since violence against the person is typically committed in proximity to the victim (although cyberbullying may constitute an exception), the concentration effect of school on violence appears to be the main driver of this type of crime. Taken together, the results in Table 4 suggest that increased robberies are the main driver behind the increased indictable violence and reduced violence against the person is the main driver of the decreased summary violence in Table 2.

5. Conclusions

A large literature has documented the beneficial effects of compulsory school attendance, one of which is reduced crime. This has been a major driver of policy in the US and elsewhere towards schooling and other youth intervention programmes aiming to support the path of human capital formation and labour market prospects, and discourage criminal participation of at-risk youth (e.g., Heller, 2014). However, little is known about the educational experience of juveniles when they are in school. Using administrative data linking education and criminal records at the individual level for juveniles in the state school system in England from 2010 to 2019, this study examines the impact of idiosyncratic school closure dates on the day-to-day propensity to commit crime of juveniles.

The empirical analysis shows that property offences and serious violence increase while minor acts of violence decrease during weekdays when school is not in session. The increased incidence of property crime is mostly driven by increased thefts. Similarly, when school is not in session a significant increase also appears in the incidence of robberies, which are serious violent offences typically committed outside school. Thus, a genuine incapacitation effect of school appears to be the prime factor governing property crime and robberies.

The reduced incidence of minor acts of violence is mostly driven by reduced assaults against the person, which typically occur in proximity to the victim. Unlike other crime categories, this reduction during school closures is hindered by the number of other schools in the locality that are not in session on the same day. This appears coherent with a concentration effect of school on violence, as it shows that violence increases when all students are forced in the same place while the greatest reduction in violence occurs when some students have to attend school and others do not.

These findings have four important implications. First, by showing that school attendance reduces indictable violence and it increases summary violence, they provide novel evidence that schools may prevent not so much the incidence but rather the severity of violence. Our analysis shows that the property and indictable violent offences that occur on school closure dates can lead to convictions in court and thus potentially set up young offenders for a criminal career. Second, by exploiting otherwise innocuous weekdays off from school, they show that in-person interactions at school are important drivers of minor acts of violence. Schools in the same locality should set their school closure dates on different weekdays, as the contemporaneous school absence for students from different schools may lead to increased assaults. Third, by showing mixed evidence of school attendance on different crime categories, our findings are consistent with the notion that reduced in-person interaction can have mixed effects on individual wellbeing. Fourth, from a policy perspective, this study highlights the need to supplement youth justice policies and compulsory school policies with services that help keep students safe and engaged in learning and prevent the potential increase in minor acts of violence on school-days documented here.

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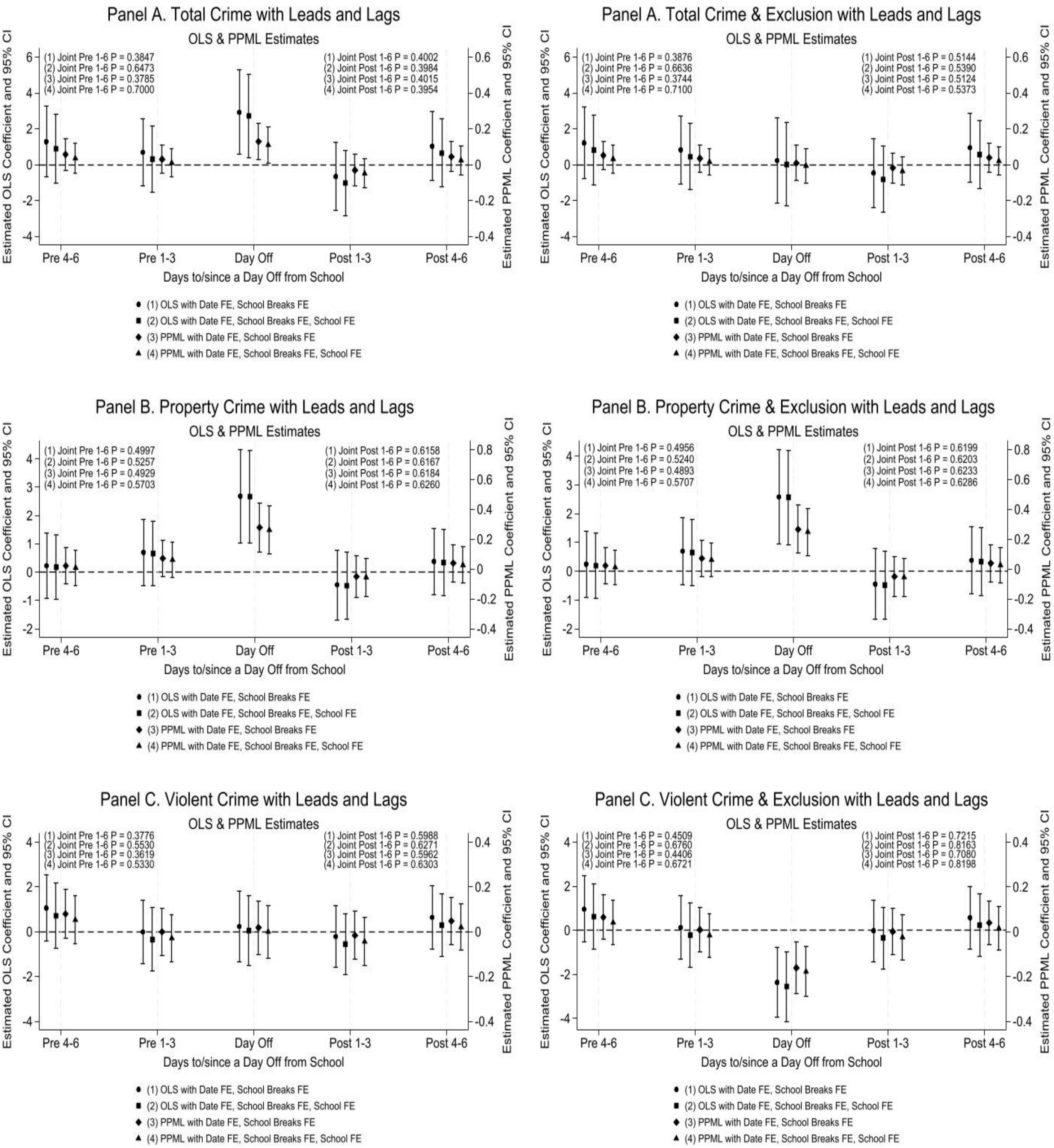
Chart 1. Estimates of the Impact of School Attendance on Count of Crimes and Permanent Exclusions with Leads & Lags



Notes: Chart displays estimates of the impact of school closures on the count of criminal offences and permanent exclusions from school. Throughout the charts, specifications (1) and (2) show Ordinary Least Squares (OLS) estimates while specifications (3) and (4) show Poisson Pseudo-Maximum Likelihood (PPML) estimates. Total exclusions are defined as the sum of permanent exclusions for property misconduct and for violent misconduct. Total crime is defined as the sum of property crime and violent crime. The left-hand side charts show results for the count of crimes while the right-hand side charts show results for the sum of the count of permanent school exclusions and the count of crimes. Panel A focuses on total crime and permanent exclusion for total misconduct, Panel B focuses on property crime and permanent exclusion for property misconduct, and Panel C focuses on violent crime and permanent exclusion for violent misconduct. For each school i, the risk of crime (or conviction) is a (0/1) dummy variable that measures whether or not any student enrolled in school i committed a criminal offence (or received a conviction) on date t. For each school i, the *count* of criminal offences (or convictions) measures the count of offences committed (or convictions received) on date t by the students enrolled in school i. School Breaks Fixed Effects (FEs) include Winter Break FEs, Spring Break FEs, Summer Break FEs. Estimated coefficients and 95% confidence intervals are displayed in the chart. Standard errors are clustered at the school level for inference. Estimates are weighted by the count of students enrolled in each school year in school. All our displayed averages and estimated coefficients are multiplied by 1000 for easier readability.

Table 1. Average Crime in the Calendar Year

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	School in Session	School Not in Session	(2)-(1)	[(2)-(1)] / [(1)/100]	Weekend	(5)-(1)	[(5)-(1)] / [(1)/100]	Winter Break	(8)-(1)	[(8)-(1)] / [(1)/100]	Spring Break	(11)-(1)	[(11)-(1)] / [(1)/100]	Summer Break	(14)-(1)	[(14)-(1)] / [(1)/100]
Panel A. Total Crime																
Risk	11.829	12.291	0.462	3.91%	10.971	-0.858	-7.25%	8.287	-3.542	-29.94%	13.250	1.421	12.01%	10.025	-1.804	-15.25%
			(0.189)			(0.088)			(0.202)			(0.244)			(0.142)	
Count	26.229	28.821	2.592	9.88%	25.810	-0.419	-1.60%	20.762	-5.467	-20.84%	31.567	5.338	20.35%	22.283	-3.946	-15.04%
			(0.613)			(0.284)			(0.712)			(0.839)			(0.440)	
Risk of Conviction	5.001	5.422	0.421	8.42%	4.891	-0.110	-2.20%	3.889	-1.112	-22.23%	5.799	0.798	15.96%	4.207	-0.794	-15.88%
			(0.126)			(0.058)			(0.133)			(0.162)			(0.092)	
Count of Convictions	16.282	18.151	1.869	11.48%	16.388	0.106	0.65%	13.824	-2.458	-15.10%	20.044	3.762	23.10%	13.579	-2.703	-16.60%
			(0.521)			(0.245)			(0.619)			(0.733)			(0.378)	
Panel B. Property Crime																
Risk	5.676	6.582	0.906	15.96%	5.795	0.119	2.10%	4.187	-1.489	-26.23%	7.198	1.522	26.81%	5.760	0.084	1.48%
			(0.135)			(0.061)			(0.139)			(0.181)			(0.101)	
Count	10.791	13.519	2.728	25.28%	11.685	0.894	8.28%	8.286	-2.505	-23.21%	14.098	3.307	30.65%	11.124	0.333	3.09%
			(0.405)			(0.169)			(0.376)			(0.478)			(0.275)	
Risk of Conviction	2.332	2.661	0.329	14.11%	2.366	0.034	1.46%	1.754	-0.578	-24.79%	2.768	0.436	18.70%	2.239	-0.093	-3.99%
			(0.087)			(0.040)			(0.088)			(0.113)			(0.066)	
Count of Convictions	6.378	7.702	1.324	20.76%	6.770	0.392	6.15%	4.825	-1.553	-24.35%	7.924	1.546	24.24%	6.235	-0.143	-2.24%
			(0.329)			(0.142)			(0.313)			(0.394)			(0.236)	
Panel C. Violent Crime																
Risk	6.876	6.402	-0.474	-6.89%	5.839	-1.037	-15.08%	4.518	-2.358	-34.29%	6.909	0.033	0.48%	4.829	-2.047	-29.77%
			(0.139)			(0.067)			(0.147)			(0.177)			(0.101)	
Count	15.438	15.302	-0.136	-0.88%	14.125	-1.313	-8.50%	12.476	-2.962	-19.19%	17.469	2.031	13.15%	11.158	-4.280	-27.72%
			(0.432)			(0.224)			(0.578)			(0.669)			(0.318)	
Risk of Conviction	2.957	3.071	0.114	3.85%	2.809	-0.148	-5.00%	2.339	-0.618	-20.90%	3.378	0.421	14.24%	2.192	-0.765	-25.87%
			(0.094)			(0.044)			(0.102)			(0.122)			(0.066)	
Count of Convictions	9.904	10.449	0.545	5.50%	9.618	-0.286	-2.89%	8.999	-0.905	-9.14%	12.120	2.216	22.38%	7.344	-2.560	-25.85%
			(0.381)			(0.196)			(0.519)			(0.606)			(0.276)	
Observations	5,885,406	509,831			3,208,512			332,446			314,381			977,584		
Dates	2,276	2,121			983			472			332			605		
Schools	3,264	3,264			3,264			3,264			3,264			3,264		

Notes: Table shows average crime risk (0/1) and counts throughout the school calendar for the period from the 1st August 2010 to the end of December 2019, when our analysis terminates. For each school i, the risk of crime (or conviction) is a (0/1) dummy variable that measures whether or not any student enrolled in school i committed a criminal offence (or received a conviction) on date t. For each school i, the *count* of criminal offences (or convictions) measures the count of offences committed (or convictions received) on date t by the students enrolled in school i. Standard errors clustered at the school level are displayed in parentheses. % Changes are measured as the estimated change deflated by the mean of the variable when school is in session displayed in column (1). Estimates are weighted by the count of students enrolled in each school year in school. All our displayed averages and estimated coefficients are multiplied by 1000 for easier readability.

Table 2. OLS Estimates of the Impact of School Attendance on the Risk (0/1) and Count of Crimes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Risk			Risk of Conviction		Count			Count of Convictions	
Panel A. Total Crime										
School Off	0.430	0.373	0.168	0.331	0.260	2.547	2.494	2.457	1.528	1.576
	(0.347)	(0.338)	(0.385)	(0.226)	(0.254)	(1.147)	(1.137)	(1.299)	(0.881)	(0.997)
School Off x Schools Off in LEA			0.050		-0.003			-0.019		-0.046
			(0.035)		(0.023)			(0.108)		(0.092)
% Effect	3.64%	3.15%	1.42%	6.62%	5.20%	9.71%	9.51%	9.37%	9.39%	9.68%
Panel B. Property Crime										
School Off	0.716	0.692	0.646	0.262	0.261	2.570	2.570	2.774	0.958	1.215
	(0.258)	(0.255)	(0.292)	(0.162)	(0.182)	(0.805)	(0.803)	(0.949)	(0.524)	(0.614)
School Off x Schools Off in LEA					-0.011			-0.063		-0.064
					(0.014)			(0.071)		(0.061)
% Effect	12.62%	12.19%	11.38%	11.24%	11.19%	23.82%	23.82%	25.71%	15.02%	19.05%
Panel C. Indictable Property Crime (or Triable Either Way)										
School Off	0.590	0.580	0.595	0.207	0.217	2.160	2.172	2.380	0.668	0.841
	(0.220)	(0.218)	(0.251)	(0.135)	(0.154)	(0.718)	(0.716)	(0.851)	(0.420)	(0.501)
School Off x Schools Off in LEA			-0.003		-0.013			-0.044		-0.060
			(0.020)		(0.013)			(0.064)		(0.058)
% Effect	14.88%	14.64%	15.01%	12.37%	12.96%	27.89%	28.04%	30.73%	14.28%	17.98%
Panel D. Summary Property Crime										
School Off	0.172	0.156	0.080	0.065	0.063	0.411	0.398	0.394	0.289	0.374
	(0.136)	(0.136)	(0.154)	(0.089)	(0.098)	(0.306)	(0.306)	(0.342)	(0.275)	(0.303)
School Off x Schools Off in LEA			0.006		0.001			-0.019		-0.005
			(0.012)		(0.006)			(0.031)		(0.018)
% Effect	9.39%	8.52%	4.37%	9.27%	8.99%	13.50%	13.07%	12.94%	17.00%	22.00%
Panel E. Violent Crime										
School Off	-0.386	-0.424	-0.543	0.104	0.036	-0.023	-0.076	-0.318	0.570	0.361
	(0.248)	(0.245)	(0.277)	(0.169)	(0.187)	(0.763)	(0.758)	(0.845)	(0.681)	(0.753)
School Off x Schools Off in LEA			0.043		0.008			0.044		0.018
			(0.026)		(0.018)			(0.078)		(0.066)
% Effect	-5.61%	-6.17%	-7.90%	3.52%	1.22%	-0.15%	-0.49%	-2.06%	5.76%	3.65%
Panel F. Indictable Violent Crime										
School Off	0.281	0.258	0.262	0.266	0.324	1.125	1.068	1.235	1.017	1.172
	(0.161)	(0.160)	(0.180)	(0.119)	(0.132)	(0.573)	(0.571)	(0.640)	(0.533)	(0.595)
School Off x Schools Off in LEA			-0.005		-0.012			-0.034		-0.030
			(0.017)		(0.013)			(0.064)		(0.056)
% Effect	10.07%	9.24%	9.39%	20.43%	24.89%	15.94%	15.13%	17.50%	20.53%	23.66%
Panel G. Summary Violent Crime										
School Off	-0.655	-0.668	-0.786	-0.213	-0.323	-1.148	-1.143	-1.552	-0.446	-0.811
	(0.198)	(0.196)	(0.216)	(0.124)	(0.138)	(0.473)	(0.469)	(0.514)	(0.407)	(0.447)
School Off x Schools Off in LEA			0.047		0.018			0.079		0.048
			(0.019)		(0.011)			(0.044)		(0.035)
% Effect	-14.83%	-15.13%	-17.8%	-12.21%	-18.51%	-13.70%	-13.64%	-18.52%	-9.01%	-16.38%
Date FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
School Breaks FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
School FE	N	Y	Y	Y	Y	N	Y	Y	Y	Y
Schools Off in LEA	N	N	Y	N	Y	N	N	Y	N	Y
Observations	11,228,160	11,228,160	11,228,160	11,228,160	11,228,160	11,228,160	11,228,160	11,228,160	11,228,160	11,228,160
Schools	3,264	3,264	3,264	3,264	3,264	3,264	3,264	3,264	3,264	3,264

Notes: Table displays Ordinary Least Squares (OLS) estimates of the impact of school closures on crime. Total crime is defined as the sum of property crime and violent crime. Columns (1)-(3) show results for the extensive margin of crime, i.e., for the risk (0/1) of crime, while columns (4) and (5) show results for the risk (0/1) of crime with a conviction in court. Columns (6)-(8) show results for the extensive and intensive margin of crime, i.e., for the count of crimes, while columns (9) and (10) show results for the count of crimes with a conviction in court. For each school i, the risk of crime (or conviction) is a (0/1) dummy variable that measures whether or not any student enrolled in school i committed a criminal offence (or received a conviction) on date t. For each school i, the *count* of criminal offences (or convictions) measures the count of offences committed (or convictions received) on date t by the students enrolled in school i. School Breaks Fixed Effects (FEs) include Winter Break FEs, Spring Break FEs, Summer Break FEs. Standard errors clustered at the school level are displayed in parentheses. For each estimated coefficient β, % effects are calculated as β deflated by the mean of the dependent variable when school is in session. Estimates are weighted by the count of students enrolled in each school year in school. All our displayed averages and estimated coefficients are multiplied by 1000 for easier readability.

Table 3. Estimates of the Impact of School Attendance on Count of Permanent Exclusions and Crimes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ordinary Least Squares					Poisson Pseudo-Maximum Likelihood		
	Permanent Exclusion		Permanent Exclusion + Crime					
	Panel A. Total Exclusions & Total Crime							
School Off	-2.691	-2.694	-0.144	-0.200	-0.465	-0.005	-0.014	-0.028
	(0.138)	(0.139)	(1.157)	(1.146)	(1.308)	(0.048)	(0.047)	(0.051)
School Off x School Off in LEA					0.044			0.003
					(0.109)			(0.005)
% Effect	-97.11%	-97.22%	-0.50%	-0.69%	-1.58%	-0.50%	-1.39%	-2.76%
Mean of Var. when School is in Session	2.771	2.771	29.387	29.387	29.387	29.387	29.387	29.387
	Panel B. Property Exclusions & Property Crime							
School Off	-0.104	-0.105	2.466	2.465	2.660	0.256	0.243	0.252
	(0.027)	(0.027)	(0.806)	(0.803)	(0.950)	(0.080)	(0.078)	(0.085)
School Off x School Off in LEA					-0.062			-0.005
					(0.071)			(0.007)
% Effect	-68.42%	-69.08%	22.54%	22.53%	24.31%	29.17%	27.51%	28.66%
Mean of Var. when School is in Session	0.152	0.152	10.941	10.941	10.941	10.941	10.941	10.941
	Panel C. Violent Exclusions & Violent Crime							
School Off	-2.587	-2.590	-2.610	-2.665	-3.125	-0.178	-0.185	-0.213
	(0.134)	(0.135)	(0.777)	(0.772)	(0.860)	(0.056)	(0.055)	(0.060)
School Off x School Off in LEA					0.105			0.008
					(0.079)			(0.007)
% Effect	-98.78%	-98.89%	-14.45%	-14.76%	-17.31%	-16.31%	-16.89%	-19.18%
Mean of Var. when School is in Session	2.619	2.619	18.062	18.062	18.062	18.062	18.062	18.062
Date FE	Y	Y	Y	Y	Y	Y	Y	Y
School Breaks FE	Y	Y	Y	Y	Y	Y	Y	Y
School FE	N	Y	N	Y	Y	N	Y	Y
Schools Off in LEA	N	N	N	N	Y	N	N	Y
Observations	11,228,160	11,228,160	11,228,160	11,228,160	11,228,160	11,228,160	11,228,160	11,228,160
Schools	3,264	3,264	3,264	3,264	3,264	3,264	3,264	3,264

Notes: Table displays estimates of the impact of school closures on the count of permanent exclusions from school and criminal offences. Columns (1)-(5) show Ordinary Least Squares (OLS) estimates while columns (6)-(8) show Poisson Pseudo-Maximum Likelihood (PPML) Estimates. Total exclusions are defined as the sum of permanent exclusions for property misconduct and for violent misconduct. Total crime is defined as the sum of property crime and violent crime. Columns (1)-(2) show results for the count of permanent school exclusions while columns (3)-(8) show results for the sum of the count of permanent school exclusions and the count of crimes. Panel A focuses on permanent exclusion for total misconduct and total crime, Panel B focuses on permanent exclusion for property misconduct and property crime, and Panel C focuses on permanent exclusion for violent misconduct and violent crime. For each school *i*, the *count* of criminal offences (or exclusions) measures the count of offences committed (or exclusions received) on date *t* by the students enrolled in school *i*. Standard errors clustered at the school level are displayed in parentheses. School Breaks Fixed Effects (FEs) include Winter Break FEs, Spring Break FEs, Summer Break FEs. In columns (1)-(5) that display OLS estimates and for each estimated coefficient β, % effects are calculated as β deflated by the mean of the dependent variable when school is in session. In columns (6)-(8) that display PPML estimates and for each estimated coefficient β, % effects are calculated as: $\%\ Effect = (\exp(\beta) - 1) * 100$. Estimates are weighted by the count of students enrolled in each school year in school. All our displayed averages and estimated coefficients are multiplied by 1000 for easier readability.

Table 4. Estimates of the Impact of School Attendance on Count of Crimes by Category

	(1)	(2)	(3)	(4)	(5)	(6)
	Ordinary Least Squares			Poisson Pseudo-Maximum Likelihood		
			Panel A. Theft			
School Off	1.605	1.620	1.652	0.330	0.321	0.314
	(0.632)	(0.630)	(0.744)	(0.123)	(0.121)	(0.131)
School Off x Schools Off in LEA			0.014			0.005
			(0.042)			(0.010)
% Effect	29.29%	29.57%	30.15%	39.10%	37.85%	36.89%
Mean Dep. Var When School is in Session	5.480	5.480	5.480	5.480	5.480	5.480
			Panel B. Criminal Damage and Arson			
School Off	0.028	0.033	0.149	0.067	0.073	0.231
	(0.127)	(0.127)	(0.132)	(0.264)	(0.259)	(0.236)
School Off x Schools Off in LEA			-0.035			-0.033
			(0.029)			(0.013)
% Effect	4.67%	5.50%	24.83%	6.93%	7.57%	25.99%
Mean Dep. Var When School is in Session	0.600	0.600	0.600	0.600	0.600	0.600
			Panel C. Burglary			
School Off	0.320	0.315	0.377	0.229	0.203	0.228
	(0.243)	(0.243)	(0.299)	(0.170)	(0.164)	(0.187)
School Off x Schools Off in LEA			-0.020			-0.011
			(0.036)			(0.022)
% Effect	21.11%	20.78%	24.87%	25.73%	22.51%	25.61%
Mean Dep. Var When School is in Session	1.516	1.516	1.516	1.516	1.516	1.516
			Panel D. Robbery			
School Off	1.352	1.316	1.463	0.528	0.505	0.497
	(0.366)	(0.363)	(0.427)	(0.125)	(0.137)	(0.145)
School Off x Schools Off in LEA			-0.038			-0.014
			(0.037)			(0.026)
% Effect	54.69%	53.24%	59.18%	69.55%	65.70%	64.38%
Mean Dep. Var When School is in Session	2.472	2.472	2.472	2.472	2.472	2.472
			Panel E. Violence Against a Person			
School Off	-0.978	-0.991	-1.250	-0.138	-0.141	-0.174
	(0.488)	(0.485)	(0.528)	(0.071)	(0.070)	(0.074)
School Off x Schools Off in LEA			0.066			0.010
			(0.045)			(0.008)
% Effect	-10.64%	-10.78%	-13.60%	-12.89%	-13.15%	-15.97%
Mean Dep. Var When School is in Session	9.192	9.192	9.192	9.192	9.192	9.192
			Panel F. Sexual Offences			
School Off	-0.263	-0.277	-0.265	-0.223	-0.237	-0.226
	(0.368)	(0.367)	(0.395)	(0.278)	(0.264)	(0.277)
School Off x Schools Off in LEA			0.004			-0.002
			(0.045)			(0.025)
% Effect	-18.40%	-19.38%	-18.54%	-19.99%	-21.10%	-20.23%
Mean Dep. Var When School is in Session	1.429	1.429	1.429	1.429	1.429	1.429
Date FE	Y	Y	Y	Y	Y	Y
School Breaks FE	Y	Y	Y	Y	Y	Y
School FE	N	Y	Y	N	Y	Y
Schools Off in LEA	N	N	Y	N	N	Y
Observations	11,228,160	11,228,160	11,228,160	11,228,160	11,228,160	11,228,160
Schools	3,264	3,264	3,264	3,264	3,264	3,264

Notes: Table displays estimates of the impact of school closures on crime by category. Columns (1)-(3) show Ordinary Least Squares (OLS) estimates while columns (4)-(6) show Poisson Pseudo-Maximum Likelihood (PPML) Estimates. Panels A, B and C focus on the crime categories that are comprised in our definition of property crime. Panels D, E and F focus on the crime categories that are comprised in our definition of violent crime. Standard errors clustered at the school level are displayed in parentheses. For each school i, the *count* of criminal offences measures the count of offences committed on date t by the students enrolled in school i. School Breaks Fixed Effects (FEs) include Winter Break FEs, Spring Break FEs, Summer Break FEs. In columns (1)-(3) that display OLS estimates and for each estimated coefficient β, % effects are calculated as β deflated by the mean of the dependent variable when school is in session. In columns (4)-(6) that display PPML estimates and for each estimated coefficient β, % effects are calculated as: $\% \, Effect = (\exp(\beta) - 1) * 100$. Estimates are weighted by the count of students enrolled in each school year in school. All our displayed averages and estimated coefficients are multiplied by 1000 for easier readability.

SUPPLEMENTAL APPENDIX

Appendix Table A.1. Average Indictable and Summary Crime in the Calendar Year by Crime Category

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	School in Session	School Not in Session	(2)-(1)	[(2)-(1)]/ [(1)/100]	Weekend	(5)-(1)	[(5)-(1)]/ [(1)/100]	Winter Break	(8)-(1)	[(8)-(1)]/ [(1)/100]	Spring Break	(11)-(1)	[(11)-(1)]/ [(1)/100]	Summer Break	(14)-(1)	[(14)-(1)]/ [(1)/100]
Panel A. Indictable Property Crime (or Triable Either Way)																
Risk	3.963	4.900	0.937	23.64%	4.085	0.122	3.08%	2.922	-1.041	-26.27%	5.219	1.256	31.69%	4.352	0.389	9.82%
			(0.116)			(0.051)			(0.115)			(0.152)			(0.087)	
Count	7.746	10.337	2.591	33.45%	8.284	0.538	6.95%	5.814	-1.932	-24.94%	10.444	2.698	34.83%	8.477	0.731	9.44%
			(0.351)			(0.137)			(0.306)			(0.407)			(0.224)	
Risk of Conviction	1.674	2.040	0.366	21.86%	1.703	0.029	1.73%	1.216	-0.458	-27.36%	2.088	0.414	24.73%	1.723	0.049	2.93%
			(0.076)			(0.033)			(0.071)			(0.097)			(0.056)	
Count of Convictions	4.678	5.924	1.246	26.64%	4.852	0.174	3.72%	3.469	-1.209	-25.84%	6.000	1.322	28.26%	4.779	0.101	2.16%
			(0.283)			(0.116)			(0.263)			(0.336)			(0.187)	
Panel B. Summary Property Crime																
Risk	1.831	1.858	0.027	1.47%	1.858	0.027	1.47%	1.357	-0.474	-25.89%	2.206	0.375	20.48%	1.540	-0.291	-15.89%
			(0.071)			(0.034)			(0.076)			(0.101)			(0.050)	
Count	3.045	3.181	0.136	4.47%	3.401	0.356	11.69%	2.471	-0.574	-18.85%	3.654	0.609	20.00%	2.648	-0.397	-13.04%
			(0.162)			(0.091)			(0.185)			(0.220)			(0.144)	
Risk of Conviction	0.701	0.685	-0.016	-2.28%	0.711	0.010	1.43%	0.573	-0.128	-18.26%	0.745	0.044	6.28%	0.564	-0.137	-19.54%
			(0.045)			(0.021)			(0.049)			(0.056)			(0.031)	
Count of Convictions	1.700	1.778	0.078	4.59%	1.918	0.218	12.82%	1.356	-0.344	-20.24%	1.924	0.224	13.18%	1.455	-0.245	-14.41%
			(0.139)			(0.077)			(0.145)			(0.185)			(0.133)	
Panel C. Indictable Violent Crime																
Risk	2.791	2.837	0.046	1.65%	2.514	-0.277	-9.92%	2.307	-0.484	-17.34%	2.986	0.195	6.99%	2.078	-0.713	-25.55%
			(0.090)			(0.042)			(0.101)			(0.117)			(0.063)	
Count	7.058	7.741	0.683	9.68%	6.947	-0.111	-1.57%	7.667	0.609	8.63%	8.324	1.266	17.94%	5.431	-1.627	-23.05%
			(0.337)			(0.171)			(0.481)			(0.521)			(0.242)	
Risk of Conviction	1.302	1.503	0.201	15.44%	1.362	0.060	4.61%	1.289	-0.013	-1.00%	1.512	0.210	16.13%	1.033	-0.269	-20.66%
			(0.067)			(0.030)			(0.075)			(0.082)			(0.045)	
Count of Convictions	4.953	5.775	0.822	16.60%	5.186	0.233	4.70%	5.826	0.873	17.63%	6.178	1.225	24.73%	3.899	-1.054	-21.28%
			(0.308)			(0.153)			(0.439)			(0.480)			(0.217)	
Panel D. Summary Violent Crime																
Risk	4.416	3.942	-0.474	-10.73%	3.621	-0.795	-18.00%	2.406	-2.010	-45.51%	4.304	-0.112	-2.54%	3.020	-1.396	-31.61%
			(0.105)			(0.052)			(0.110)			(0.141)			(0.076)	
Count	8.380	7.561	-0.819	-9.77%	7.178	-1.202	-14.34%	4.809	-3.571	-42.61%	9.145	0.765	9.13%	5.728	-2.652	-31.65%
			(0.249)			(0.135)			(0.290)			(0.399)			(0.182)	
Risk of Conviction	1.745	1.673	-0.072	-4.13%	1.531	-0.214	-12.26%	1.109	-0.636	-36.45%	1.958	0.213	12.20%	1.210	-0.535	-30.66%
			(0.068)			(0.032)			(0.069)			(0.095)			(0.047)	
Count of Convictions	4.952	4.674	-0.278	-5.61%	4.432	-0.520	-10.50%	3.173	-1.779	-35.92%	5.942	0.990	19.99%	3.445	-1.507	-30.43%
			(0.214)			(0.117)			(0.258)			(0.362)			(0.159)	
Observations	5,885,406	509,831			3,208,512			332,446			314,381			977,584		
Dates	2,276	2,121			983			472			332			605		
Schools	3,264	3,264			3,264			3,264			3,264			3,264		

Notes: Table shows average crime risk (0/1) and counts by category throughout the school calendar for the period from the 1st August 2010 to the end of December 2019, when our analysis terminates. For each school i, the risk of crime (or conviction) is a (0/1) dummy variable that measures whether or not any student enrolled in school i committed a criminal offence (or received a conviction) on date t. For each school i, the *count* of criminal offences (or convictions) measures the count of offences committed (or convictions received) on date t by the students enrolled in school i. Standard errors in parentheses are clustered at the school level. % Changes are measured as the estimated change deflated by the mean of the variable when school is in session displayed in column (1). Estimates are weighted by the count of students enrolled in each school year in school. All our displayed averages and estimated coefficients are multiplied by 1000 for easier readability.

Appendix Table A.2. Probit Estimates of the Impact of School Attendance on the Risk of Crime (0/1)

	(1)	(2)	(3)	(4)	(5)
		Risk		Risk of Conviction	
			Panel A. Total Crime		
School Off	0.017	0.015	0.008	0.028	0.021
	(0.014)	(0.014)	(0.015)	(0.019)	(0.020)
School Off x			0.002		0.000
Schools Off in LEA			(0.002)		(0.002)
% Effect	4.53%	3.63%	1.86%	7.86%	5.76%
			Panel B. Property Crime		
School Off	0.053	0.052	0.050	0.045	0.044
	(0.019)	(0.019)	(0.020)	(0.026)	(0.028)
School Off x			0.000		-0.001
Schools Off in LEA			(0.002)		(0.002)
% Effect	15.47%	14.42%	14.08%	13.72%	13.26%
			Panel C. Indicatable Property Crime (or Triable Either Way)		
School Off	0.060	0.061	0.062	0.049	0.049
	(0.022)	(0.022)	(0.024)	(0.031)	(0.033)
School Off x			0.000		0.000
Schools Off in LEA			(0.002)		(0.002)
% Effect	18.54%	17.79%	18.25%	15.42%	15.29%
			Panel D. Summary Property Crime		
School Off	0.034	0.029	0.018	0.031	0.029
	(0.027)	(0.027)	(0.030)	(0.043)	(0.046)
School Off x			0.001		0.001
Schools Off in LEA			(0.003)		(0.004)
% Effect	11.26%	9.03%	5.59%	10.00%	9.36%
			Panel E. Violent Crime		
School Off	-0.024	-0.028	-0.036	0.014	0.003
	(0.016)	(0.016)	(0.018)	(0.022)	(0.024)
School Off x			0.003		0.002
Schools Off in LEA			(0.002)		(0.003)
% Effect	-6.58%	-7.27%	-9.25%	4.09%	0.76%
			Panel F. Indictable Violent Crime		
School Off	0.038	0.036	0.034	0.072	0.078
	(0.021)	(0.022)	(0.024)	(0.031)	(0.032)
School Off x			0.000		-0.003
Schools Off in LEA			(0.003)		(0.004)
% Effect	12.20%	10.83%	10.19%	23.90%	26.13%
			Panel G. Summary Violent Crime		
School Off	-0.065	-0.069	-0.081	-0.048	-0.072
	(0.020)	(0.020)	(0.022)	(0.029)	(0.032)
School Off x			0.006		0.005
Schools Off in LEA			(0.003)		(0.004)
% Effect	-17.41%	-17.75%	-20.53%	-13.73%	-19.75%
Date FE	Y	Y	Y	Y	Y
School Breaks FE	Y	Y	Y	Y	Y
School FE	N	Y	Y	Y	Y
Schools Off in LEA	N	N	Y	N	Y
Observations	11,228,160	11,228,160	11,228,160	11,228,160	11,228,160
School	3,264	3,264	3,264	3,264	3,264

Notes: Table displays Probit estimates of the impact of school closures on crime. Total crime is defined as the sum of property crime and violent crime. Columns (1)-(3) show results for the extensive margin of crime, i.e., for the count of crimes, while columns (4) and (5) show results for the extensive margin of crime with a conviction in court. For each school i, the risk of crime (or conviction) is a (0/1) dummy variable that measures whether or not any student enrolled in school i committed a criminal offence (or received a conviction) on date t. School Breaks Fixed Effects (FEs) include Winter Break FEs, Spring Break FEs, Summer Break FEs. Standard errors clustered at the school level are displayed in parentheses. For each estimated coefficient β, % effects are calculated as the marginal effect from the Probit estimates. Estimates are weighted by the count of students enrolled in each school year in school. All our displayed averages and estimated coefficients are multiplied by 1000 for easier readability.

Appendix Table A.3. PPML Estimates of the Impact of School Attendance on the Count of Crimes

	(1)	(2)	(3)	(4)	(5)
		Count		Count of Convictions	
			Panel A. Total Crime		
School Off	0.113	0.103	0.094	0.099	0.091
	(0.050)	(0.049)	(0.053)	(0.060)	(0.064)
School Off x			0.001		-0.002
Schools Off in LEA			(0.005)		(0.007)
% Effect	11.96%	10.85%	9.86%	10.41%	9.53%
			Panel B. Property Crime		
School Off	0.269	0.256	0.266	0.160	0.182
	(0.080)	(0.078)	(0.085)	(0.089)	(0.095)
School Off x			-0.005		-0.008
Schools Off in LEA			(0.007)		(0.009)
% Effect	30.87%	29.18%	30.47%	17.35%	19.96%
			Panel C. Indicatable Property Crime (or Triable Either Way)		
School Off	0.312	0.300	0.311	0.152	0.169
	(0.098)	(0.096)	(0.104)	(0.098)	(0.106)
School Off x			-0.004		-0.010
Schools Off in LEA			(0.008)		(0.010)
% Effect	36.62%	34.99%	36.48%	16.42%	18.41%
			Panel D. Summary Property Crime		
School Off	0.159	0.141	0.141	0.184	0.221
	(0.114)	(0.110)	(0.116)	(0.172)	(0.177)
School Off x			-0.006		0.000
Schools Off in LEA			(0.010)		(0.014)
% Effect	17.23%	15.14%	15.14%	20.20%	24.73%
			Panel E. Violent Crime		
School Off	-0.001	-0.009	-0.031	0.061	0.031
	(0.058)	(0.058)	(0.062)	(0.077)	(0.082)
School Off x			0.005		0.004
Schools Off in LEA			(0.007)		(0.010)
% Effect	-0.10%	-0.90%	-3.05%	6.29%	3.15%
			Panel F. Indictable Violent Crime		
School Off	0.172	0.160	0.166	0.207	0.211
	(0.084)	(0.085)	(0.090)	(0.109)	(0.115)
School Off x			-0.005		-0.005
Schools Off in LEA			(0.012)		(0.015)
% Effect	18.77%	17.35%	18.06%	23.00%	23.49%
			Panel G. Summary Violent Crime		
School Off	-0.173	-0.173	-0.229	-0.117	-0.196
	(0.074)	(0.073)	(0.078)	(0.103)	(0.112)
School Off x			0.014		0.014
Schools Off in LEA			(0.009)		(0.012)
% Effect	-15.89%	-15.89%	-20.47%	-11.04%	-17.80%
Date FE	Y	Y	Y	Y	Y
School Breaks FE	Y	Y	Y	Y	Y
School FE	N	Y	Y	Y	Y
Schools Off in LEA	N	N	Y	N	Y
Observations	11,228,160	11,228,160	11,228,160	11,228,160	11,228,160
School	3,264	3,264	3,264	3,264	3,264

Notes: Table displays Poisson Pseudo-Maximum Likelihood (PPML) estimates of the impact of school closures on crime. Total crime is defined as the sum of property crime and violent crime. Columns (1)-(3) show results for the extensive and intensive margin of crime, i.e., for the count of crimes, while columns (4) and (5) show results for the count of crimes with a conviction in court. For each school *i*, the *count* of criminal offences (or convictions) measures the count of offences committed (or convictions received) on date *t* by the students enrolled in school *i*. School Breaks Fixed Effects (FEs) include Winter Break FEs, Spring Break FEs, Summer Break FEs. Standard errors clustered at the school level are displayed in parentheses. For each estimated coefficient β, % effects are calculated as: $\% Effect = (\exp(\beta) - 1) * 100$. Estimates are weighted by the count of students enrolled in each school year in school. All our displayed averages and estimated coefficients are multiplied by 1000 for easier readability.

Appendix Table A.4 OLS Estimates of the Impact of School Attendance on the Count of Crimes per Student

	(1)	(2)	(3)	(4)	(5)
		Count		Count of Convictions	
			Panel A. Total Crime		
School Off	0.025	0.027	0.026	0.018	0.018
	(0.012)	(0.012)	(0.013)	(0.009)	(0.010)
School Off x			0.000		-0.001
Schools Off in LEA			(0.001)		(0.001)
% Effect	9.09%	9.82%	9.46%	10.53%	10.53%
			Panel B. Property Crime		
School Off	0.025	0.026	0.028	0.010	0.013
	(0.008)	(0.008)	(0.010)	(0.005)	(0.006)
School Off x			-0.001		-0.001
Schools Off in LEA			(0.001)		(0.001)
% Effect	22.12%	23.01%	24.78%	14.93%	19.40%
			Panel C. Indictable Property Crime (or Triable Either Way)		
School Off	0.022	0.023	0.025	0.008	0.010
	(0.007)	(0.007)	(0.009)	(0.004)	(0.005)
School Off x			-0.001		-0.001
Schools Off in LEA			(0.001)		(0.001)
% Effect	27.16%	28.40%	30.86%	16.33%	20.41%
			Panel D. Summary Property Crime		
School Off	0.003	0.003	0.003	0.002	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
School Off x			0.000		0.000
Schools Off in LEA			(0.000)		(0.000)
% Effect	9.38%	9.38%	9.38%	11.11%	16.67%
			Panel E. Violent Crime		
School Off	0.000	0.001	-0.002	0.007	0.005
	(0.008)	(0.008)	(0.009)	(0.007)	(0.008)
School Off x			0.001		0.000
Schools Off in LEA			(0.001)		(0.001)
% Effect	0.00%	0.62%	-1.24%	6.73%	4.81%
			Panel F. Indictable Violent Crime		
School Off	0.012	0.012	0.014	0.011	0.013
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)
School Off x			0.000		0.000
Schools Off in LEA			(0.001)		(0.001)
% Effect	16.22%	16.22%	18.92%	21.15%	25.00%
			Panel G. Summary Violent Crime		
School Off	-0.012	-0.011	-0.016	-0.004	-0.008
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)
School Off x			0.001		0.000
Schools Off in LEA			(0.000)		(0.000)
% Effect	-13.64%	-12.50%	-18.18%	-7.69%	-15.39%
Date FE	Y	Y	Y	Y	Y
School Breaks FE	Y	Y	Y	Y	Y
School FE	N	Y	Y	Y	Y
Schools Off in LEA	N	N	Y	N	Y
Observations	11,228,160	11,228,160	11,228,160	11,228,160	11,228,160
Schools	3,264	3,264	3,264	3,264	3,264

Notes: Table displays Ordinary Least Squares (OLS) estimates of the impact of school closures on crime deflated by the count of students enrolled in each school. Total crime is defined as the sum of property crime and violent crime. Columns (1)-(3) show results for the extensive and intensive margin of crime, i.e., for the count of crimes, while columns (4) and (5) show results for the count of crimes with a conviction in court. For each school i, the *count* of criminal offences (or convictions) measures the count of offences committed (or convictions received) on date t by the students enrolled in school i. School Breaks Fixed Effects (FEs) include Winter Break FEs, Spring Break FEs, Summer Break FEs. Standard errors clustered at the school level are displayed in parentheses. For each estimated coefficient β, % effects are calculated as β deflated by the mean of the dependent variable when school is in session. Estimates are weighted by the count of students enrolled in each school year in school. All our displayed averages and estimated coefficients are multiplied by 10000 for easier readability.

Appendix Table A.5. PPML Estimates of the Impact of School Attendance on the Count of Crimes per Student

	(1)	(2) Count	(3)	(4)	(5) Count of Convictions
			Panel A. Total Crime		
School Off	0.105	0.110	0.102	0.111	0.105
	(0.048)	(0.048)	(0.052)	(0.059)	(0.062)
School Off x			0.000		-0.003
Schools Off in LEA			(0.005)		(0.007)
% Effect	11.07%	11.63%	10.74%	11.74%	11.07%
			Panel B. Property Crime		
School Off	0.248	0.254	0.265	0.167	0.195
	(0.079)	(0.078)	(0.085)	(0.083)	(0.089)
School Off x			-0.006		-0.011
Schools Off in LEA			(0.007)		(0.009)
% Effect	28.15%	28.92%	30.34%	18.18%	21.53%
			Panel C. Indictable Property Crime (or Triable Either Way)		
School Off	0.303	0.312	0.323	0.181	0.200
	(0.098)	(0.097)	(0.105)	(0.095)	(0.102)
School Off x			-0.007		-0.013
Schools Off in LEA			(0.009)		(0.011)
% Effect	35.39%	36.62%	38.13%	19.84%	22.14%
			Panel D. Summary Property Crime		
School Off	0.103	0.102	0.108	0.127	0.193
	(0.102)	(0.099)	(0.106)	(0.157)	(0.161)
School Off x			-0.003		-0.002
Schools Off in LEA			(0.009)		(0.013)
% Effect	10.85%	10.74%	11.40%	13.54%	21.29%
			Panel E. Violent Crime		
School Off	0.002	0.007	-0.016	0.076	0.045
	(0.057)	(0.057)	(0.061)	(0.076)	(0.081)
School Off x			0.005		0.004
Schools Off in LEA			(0.007)		(0.010)
% Effect	0.20%	0.70%	-1.59%	7.90%	4.60%
			Panel F. Indictable Violent Crime		
School Off	0.173	0.174	0.182	0.223	0.229
	(0.084)	(0.085)	(0.089)	(0.109)	(0.113)
School Off x			-0.004		-0.004
Schools Off in LEA			(0.011)		(0.015)
% Effect	18.89%	19.01%	19.96%	24.98%	25.73%
			Panel G. Summary Violent Crime		
School Off	-0.169	-0.157	-0.217	-0.104	-0.188
	(0.072)	(0.071)	(0.077)	(0.101)	(0.110)
School Off x			0.013		0.012
Schools Off in LEA			(0.008)		(0.011)
% Effect	-15.55%	-14.53%	-19.51%	-9.88%	-17.14%
Date FE	Y	Y	Y	Y	Y
School Breaks FE	Y	Y	Y	Y	Y
School FE	N	Y	Y	Y	Y
Schools Off in LEA	N	N	Y	N	Y
Observations	11,228,160	11,228,160	11,228,160	11,228,160	11,228,160
Schools	3,264	3,264	3,264	3,264	3,264

Notes: Table displays Poisson Pseudo-Maximum Likelihood (PPML) estimates of the impact of school closures on crime deflated by the count of students enrolled in each school. Total crime is defined as the sum of property crime and violent crime. Columns (1)-(3) show results for the extensive and intensive margin of crime, i.e., for the count of crimes, while columns (4) and (5) show results for the count of crimes with a conviction in court. For each school *i*, the *count* of criminal offences (or convictions) measures the count of offences committed (or convictions received) on date *t* by the students enrolled in school *i*. School Breaks Fixed Effects (FEs) include Winter Break FEs, Spring Break FEs, Summer Break FEs. Standard errors clustered at the school level are displayed in parentheses. For each estimated coefficient β, % effects are calculated as: $\%\ Effect = (\exp(\beta) - 1) * 100$. Estimates are weighted by the count of students enrolled in each school year in school. All our displayed averages and estimated coefficients are multiplied by 10000 for easier readability.

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