Why Do Kids Get into Trouble on School Days?

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Abstract

Previous literature highlights a robust relationship between schools and longer term criminal outcomes. The research presented here examines the short term effects of school being in-session on crime. We begin by confirming the findings of Jacob & Lefgren (2003) that teacher in-service days lead to a reduction in violent crime, consistent with a role for social interactions in school. We extend this result by showing that schools populated with more high crime risk students have larger decreases in crime on teacher in-service days but that this effect is reversed for schools with mostly low crime risk students. These results provide evidence that concentrating high crime risk students into particular schools increases local crime.

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1 Introduction

The presence and variation in crime across urban neighborhoods is often attributed to such diverse factors as police enforcement, lack of legal employment opportunities and the presence of social environments that lower the cost of crime. Numerous policy attempts to improve criminal justice procedures and provide better employment opportunities have not made large impacts on neighborhoods with persistently high levels of crime. Given the challenges in addressing this spatial inequality in crime, a number of policies have begun to leverage the role of social influences on criminal decisions. As discussed by **?**, patterns of crime across neighborhoods and over time display strong evidence of social interactions. Given the role of public schools in grouping kids together, school assignment policies have an important role in facilitating social influences on crime. The common policy of neighborhood assignment to schools generates a strong link between school interactions and neighborhood crime. Therefore, policies that impact school assignment or even school attendance calendars may have importance roles in addressing spatial inequality in crime.

Schools provide two distinct mechanisms for affecting juvenile crime. Compulsory schooling is a form of incapacitation for juveniles that both educates and provides activities for otherwise 'idle hands'. This incapacitation effect is coupled with social interactions that often form due to relationships created during school. Decoupling the effects of incapacitation and social interactions due to schools is challenging, and most of our understanding of school social interactions and crime is based on longer-term effects of school peers on adult crime (e.g. **?**, **?**, **?**, **?**, **?**). In contrast, our understanding of incapacitation is primarily based on non-school, limited interaction settings such as movies or video games where **?** and **?** show that the release of popular movies or video games keeps juveniles occupied and leads to a decrease or no effect on crime.

Most scholars find a negative relationship between schools and crime with most of this research focusing on school peer quality. **?** and **?** show that kids assigned to a better school under school choice lotteries are less likely to be arrested as adults. This finding is confirmed in different contexts with **?** and **?** showing that school peer composition matters for offending and direct peer interactions. Some longer-term studies support the role of incapacitation. Using variation in the length of schools days, **?** shows that longer school days decrease adult crime. This effect is taken as an incapacitation effect, since a larger dosage of peer interaction due to a prolonged school day would increase any peer effects in the opposite direction. A number of other papers show the positive effects on staying in school longer on crime which may highlight benefits due to incapacitation.[2]

Other scholars confirm or suggest a role for peers and crime outside schools. **?** show a positive relationships between military service and later crime which may be a result of negative peer effects in the military. **?** find a positive effect of youth employment programs in decreasing later crime with peers being one of the underlying mechanisms. Additionally, **?** show a large role of peer effects on recidivism due to juvenile incarceration. Almost all of the literature on schools and crime focuses on longer-term criminal outcomes, which are often a result of years together in school as well as multiple social interactions. These long-term impacts are important for policies that relate to school assignment and school resources.

In contrast only a few studies examine the short-term effects of school on crime. In its simplest form, short term effects could be staying off the street during school hours or hanging out with school friends after school. **?** shows that in-service (teacher work) days lead to less violent crime and more property crime with most of the effects due to less after school violent crime.[3] This finding of less school leading to less violent crime dismisses a strong role for incapacitation, while the finding of greater property crime is suggestive of some benefits due to incapacitation. **?** provides support for the results in **?** by showing teacher strikes and the associated canceling of school leads to decreases in violent crime and increases in property crimes. **?** finds that kids subject to out-of-school suspension have twice the rate of offending relative to kids with in-school suspension.

This literature provides strong evidence for the short-term effects of schools on crime, but more analysis is needed to understand temporal and spatial heterogeneity in this relationship. Do certain neighborhoods experience different

[2]e.g. **?**, **?**, **?**

[3]The term in-service and teacher work day are synomous and both indicate weekdays during the school year set aside for teacher planning and entail teachers going to the school, but no students attend school for the day.

effects from variation in school days? How does the timing of crime change in response to having the day off from school? If juveniles are not in school, they are likely in home neighborhoods thus potentially changing peer concentration and the subsequent nature of peer effects. Since policy recommendations are quite different for the short-term effects of schools on crime, additional evidence is needed to better tailor policies such as after-school programs, police deployment, and school calendar configurations (length of day, number of school days) to minimize crime outcomes.

The research presented here first applies the model of **?** to a different dataset and study area and confirms most of their results. Our contribution then lies in expanding this model of exogenous variation in schooling due to teacher in-service days to examine the composition of students by neighborhood and schools, the location of crime, and changes in crime clearance on in-service days. These additional elements provide new insight into the role of schools. Specifically, heterogeneity in the response of crime to school closures highlights the strong role of schools on increasing violent crime in neighborhoods with large shares of high crime risk students. Consistent with **?**, this result highlights a role of both schools and neighborhoods among likely criminals for which schools provide a means to facilitate social interaction. Conversely, schools populated by low crime risk students decrease crime levels, suggesting a role for positive peer effects on decreasing crime. The timing of crime effects confirms that the role of schools is primarily through facilitating social interactions during school which spillover into after-school hours. Finally, we examine crime clearance on in-service days, and find no effects once we control for the changing composition of crime types, suggesting police adapt to changing activity patterns of students.

2 Data

Since we want to extend existing analysis of the short-term effects of school on crime, we need more spatially detailed data then is provided in datasets such as the National Incident-Based Reporting System. We therefore turn to the administrative set of a large urban policing district located in Charlotte, NC which contains a population of around 1 million people and receives almost

100,000 reported crimes a year. Our main dataset is based on reported crime records from the Charlotte-Mecklenburg Police Department (CMPD), which maintains an extensive database on reported crimes. Similar in nature to the National Incident-Based Reporting System data, this dataset contains detailed information about the time, day and nature of each reported crime in our study area of Charlotte which encompasses almost of all of Mecklenburg County, NC. The main advantage of this data is two additional features. First, we have the exact spatial coordinates for the reported location of each crime. Second, we are able to determine if a crime led to an arrest or was dismissed as a non-criminal activity. We incorporate data from 1998-2011 which corresponds with the 1998/1999 through 2010/2011 school years. We start with a total of 1,479,910 reported crimes into our analysis and use geographical information to assign reported crime to 372 Census Block Groups. After removing any observations for incidents that are noncriminal, suicide/accidental death, missing person or runaway, or contained missing information we had 1,408,265 observations. Consistent with the literature, we classify crime by FBI crime categories and focus on indexed property and violent crimes.

Since our reported crimes data does not contain information on offenders, we also incorporate data on arrests of juveniles aged 16-18. We take an extract from the Mecklenburg County Sheriff's Department which serves the same jurisdiction as the CMPD. This dataset will provide fewer events but is better suited to identify juvenile criminal activity. Results using reported crime and juvenile arrests are similar and most of our results focus on reported crimes since they capture more criminal events and are not as heavily influenced by arrest rates.

Our final source of data is school administrative records for the schools years of 1999-2011 from Charlotte-Mecklenburg Schools (CMS) for all individual students that attended public school in the county. The data include student gender, race, yearly end-of-grade (EOG) test scores, days absent and days suspended from school. The EOG tests are standardized and administered across the state of North Carolina from 1993 to the present. We link CMS data to arrest registry data for Mecklenburg County from 1999 to 2011 using first and last name as well as date of birth. The arrest data includes individual names and identifiers, and information on the number and nature of charges. While this data allow us to observe the future criminal behavior of CMS students, regardless of whether they transfer or drop out of school, they are limited to crimes committed within Mecklenburg County.

We use the CMS data to determine the number of students living in a neighborhood and also match school and arrest data to determine predicted arrest risk factors for CMS students. In order to generate predicted arrest probabilities, we estimate a first stage model of an individual ever being arrest between the ages of 16 and 21 on covariates for gender, race, math and reading test scores in 5th grade, days absent and days suspended from school in 5th grade. We also include year fixed effects and CBG neighborhood fixed effects. We limit the sample used to estimate the coefficients that explain arrest probabilities to students that we observe at age 14 between the 1999-2001 school years to avoid any confounding effects from the large change in school attendance boundaries that occurred in 2003. We then use these coefficients to generate predicted arrest probabilities for all students in the 1999-2011 school years and classify any student with a predicted arrest probability in the top quintile as 'very high risk'.

Table 1 provides descriptive statistics for our panel dataset of daily observations for each CBG neighborhood. Our data averages about 0.65 incidents and 0.014 juvenile arrests per day for our 372 CBG neighborhoods. About two-thirds of reported crimes are classified as property crimes while about one-sixth are violent crimes. For different time blocks of a day, we see reported crimes evenly distributed across daytime hours as well as afternoon/evening hours. Not surprisingly, reported crimes are less frequent during the early morning hours.

3 Empirical Framework

Our empirical strategy exploits teacher in-service work days to create quasi-experimental variation in whether school is in session. We claim that the Charlotte-Mecklenburg school system assigns in-service days within the school year as good as randomly, conditional on covariates. Comparing crime rates on in-service days to days for which school is in session will allow us to measure how putting juveniles in school affects the level, timing, and location of crimes.

This identification strategy has been used and justified as valid by **?**. We will also demonstrate that in-service days provide a valid source of exogenous variation in the present data.

We begin by using variation in teacher in-service days to test whether city-wide crime levels increase or decrease when school is in session. In-service days are not assigned completely at random to days in the year, but we can control for how the non-random components of days of the week and time of year affect crime. As shown in Table 1, in-service days do not occur during summer break or on weekends. The school system also tends to assign in-service days according to convenience. Fifteen percent of in-service days occur on national holidays, though holidays only cover 2.5 percent of the year, and 61 percent of in-service days extend a weekend by occurring on a Monday or Friday.[4] Thus, our empirical model will include relevant controls for days of the week and holidays. Formally, we will estimate the following model:

$$Y_{wd} = \beta_0 + \beta_1 T_{wd} + \delta X_{wd} + \psi_w + \omega_d + \epsilon_{wd} \qquad (1)$$

In this model, all variables are measured as city-wide totals for day of the week d during week w. Y_{wd} is an outcome, e.g. the number of crime incidents reported. T_{wd} is our treatment of interest, an indicator for whether the day is an in-service work day for teachers. We include day of the week and week-year fixed effects ω_d and ψ_w. The coefficient of interest is β_1, which can be interpreted as a generalized difference-in-differences estimate of the difference in crime levels between in-service days and other days. We also control for some characteristics X_{wd} that vary by date including dummies for other days off school (summer break, days off denoted as holidays, and days off denoted as leave days like spring break) and a dummy for national holidays. Our estimated in-service effects will thus compare in-service days to other days when school is in session, adjusting for the tendency of in-service days to fall on holidays, particular days of the week, and particular weeks.

[4]One may be surprised to find in-service days occurring on national holidays, but we define holidays based on days the stock market is closed during the week which includes some holidays not recognized by the school system.

Our empirical strategy relies on the claim that in-service days are as good as randomly assigned to days, conditional on our covariates. The planning and timing of in-service days is know beforehand to parents. The main issue would be if this led to large changes in the behavior of juveniles or parents prior to in-service days. Parents would need to stay home for younger children, but this is less of a concern with respect to the age profile of crime with criminal behavior really only beginning among middle school children. Furthermore, parents of high crime risk children often have more limited resources and thus are unable to forgo work and income for the family. The nature of our study is on the short-term impacts of crime, and thus we are less concerned with substitution patterns in criminal activity in the days preceding/following in-service days. We rather focuses our analysis on the immediate effects of the removal of school incapacitation and social interactions due to in-service days. To help verify that we have properly controlled for factors that may influence the choice of in-service days and crime, we also run a placebo test showing that days one week after and one week before in-service days have crime levels similar to a typical school day.

In the present paper, we push beyond measuring the overall effect of school being in session on crime levels to examine how school days affect crime locations. As a first step, we use detailed crime location data to create a Census block group (CBG) by day panel of crime incidents for the city of Charlotte. We can then measure the average effect of in-service days on crime using the panel dataset:

$$Y_{iwd} = \beta_0 + \beta_1 T_{wd} + \delta X_{wd} + \psi_w + \omega_d + \alpha_i + u_{iwd} \qquad (2)$$

All variables are defined as above, though now i denotes CBG, outcomes are measured at the CBG-day level, and we can control for CBG fixed effects, α_i. The real value of panel data, though, is to examine whether and how in-service days affect crime in different neighborhoods. We can add some vector of observable neighborhood characteristics S_{wdt} and the interaction of these characteristics with in-service days:

$$Y_{iwd} = \beta_0 + \beta_1 T_{wd} + \gamma S_{iwd} + \phi S_{iwd} * T_{wd} + \delta X_{wd} + \psi_w + \omega_d + \alpha_i + u_{iwd} \tag{3}$$

The vector of coefficients ϕ indicates whether in-service days increase or decrease crime more in neighborhoods with certain characteristics. In particular, we will consider the number of students living and/or attending school in the CBG as well as whether observable characteristics of those students indicate that they are at high risk for committing crime. Using equation **??**, we can test whether the effect of letting school out for the day depends on the characteristics of the students at the school or in the neighborhood. Equivalently, we can split the sample based on values of S_{iwd} and estimate equation **??** on sub-samples.

4 Results

4.1 Average Effect of Closing School

We implement the empirical strategy described above and measure how crime levels change when the Charlotte-Mecklenburg school system closes for teacher in-service days. This specification essentially replicates the results of **?** in the context of our data. Table **??** shows the results of applying the model in equation **??** to a city-wide daily time series of reported crime incidents. The coefficient on an in-service day dummy variable identifies the average difference in reported crime levels between in-service days and other school days. Column (1) shows results controlling for differences generated by day of the week and week-year effects. We find that in-service days generate 10.1 fewer reported crimes. On an average day, the data reports 243.2 incidents across the city of Charlotte, so in-service days decrease reported crime by 4.2 percent. As shown in column (2), adding summer and holiday controls shows a similar value of 9.7, i.e. 4.0 percent.

The remaining columns of Table **??** show what types of crime drive our results. Violent crimes drop by 3.1 crimes (7 percent) on in-service days while property crimes decrease by only a statistically insignificant 2.1 crimes (1 percent) per day despite being much more common. Other crimes against neither person nor property also fall significantly. In the Appendix, Table **??** splits out these effects by more detailed crime types. Large decreases in assaults and sex offenses drive the drop in violent crime. Drug crimes do not drive the drop in “other crimes;” instead, this is partially driven by a decrease in weapons violations as well as by a large number of relatively infrequent crimes. Our measured insignificant change in property crimes hides some heterogeneity in the underlying categories. Burglaries and forgery/fraud incidents drop significantly on in-service days while instances of vandalism increase.

We repeat this city-wide analysis using juvenile arrests in the bottom panel of Table **??**. Even though we need to incorporate our reported crime dataset to highlight both the time and location of crime, we want to make sure that results would be similar using a more juvenile specific measure of crime, namely our arrest data on 16-18 year old offenders. Thus, in the bottom panel we replicate the city-wide results using juvenile arrests as the outcome. We find similar results with overall incidents and juvenile arrests. Columns (1) and (2) show that juvenile arrests fall by 16 percent or 19 percent overall, depending on the specification. As before, the effects are concentrated with violent crimes rather than property crimes. Juvenile arrests for violent crimes fall by 33 percent while juvenile arrests for property crimes actually increase insignificantly by 6 percent. Arrests for other types of crime fall by 29 percent.

Finally, we replicate the previous analysis using a panel in which we measure crime for each day in each Census Block Group (CBG). This panel will be useful later when we consider how closing school affects crimes in different locations depending on the characteristics of the neighborhood. For the moment, Table **??** simply replicate the results of Table **??** using this CBG by day panel and the specification in equation **??**. For clarity of reading, we report all CBG-level results with the outcome multiplied by 100. The results are almost identical to those using city-wide crime counts. Column (2) of the top panel of Table **??** indicates that incidents fall by 4.0 percent on in-service days. The bottom panel shows that juvenile arrests decrease by 21 percent. Both panels re-enforce our result that violent crime rather than property crime drives this result.

Broadly speaking, our results are consistent with those found by **?**. They find that closing school for teacher in-service days decreases violent crime by 31 percent and increases property crime by a statistically insignificant 7 percent. Our results differ somewhat from those of **?** in that we find a drop in total crime, while they find that competing effects for property and violent crimes essentially cancel each other. This different result for property crimes may be due to differences across these two studies in terms of study area, time periods, and the mix of crime categories.[5] Overall, our results tell a very similar story. Closing school noticeably decreases violent crime. Rather than incapacitating juveniles who would otherwise commit violent crimes, having school in session increases social interaction which leads to increases in violent crimes.

4.2 Placebo Test

We provide an additional test that the Charlotte-Mecklenburg school system assigns teacher in-service days in a manner unrelated to crime levels, conditional on our covariates. We consider placebo days one week before and one week after actual teacher in-service days and examine whether crime on these days differ from other days. Table **??** replicates the specification in Table **??** replacing the in-service day dummy with a dummy for whether an in-service day occurred one week prior. Contrary to our main results, the coefficient on the lagged in-service dummy is slightly positive in all specifications, though small and statistically insignificant. Crime levels appear similar on these placebo days when school is actually in session. Table **??** also shows similar results for an indicator of whether there is an in-service day one week in the future. The coefficients here are negative, which would be concerning if it indicates that crime begins falling in anticipation of future in-service days. However, these effects are not only statistically insignificant but also only one-third of the main effects we measure. Reported incidents of violent and other crimes, the types which drive our main results, are balanced in the week leading up to an in-service day. Overall, in-service days do not predict future or past crimes levels. This result provides some confirmation that school closure drives the differences in crime levels between in-service days and other days rather than crime trends around the peculiarities of which days are chosen to let out school.

[5] We found that if we focus on likely juvenile crimes such as vandalism that we get positive effects in our dataset, but these effects disappear or become negative for other property crimes such as burglary and forgery/fraud.

5 Mechanisms

We can apply the rich data available for the case of Charlotte, North Carolina to more closely investigate why violent crime falls when school is not in-session. The timing and location of crime is informative about how staying home from school impacts criminal interaction between juveniles. Furthermore, this information is useful for examining the role of policing which may re-allocate resources in response to the relocation of juveniles away from schools. Using data on the timing, location, and clearance rates of crimes, we can investigate the mechanism by which closing school affects crime levels.

5.1 Time of Day

The time of day that a crime occurs can shed light on why school being in-session leads to more violent crime. If in-service days lead to less crime only during school hours, then it could be that the simple act of concentrating many people in one place generates crime in that location (e.g. creating fights at school). However, if whether school is in session affects crime after school, then it may be that school fosters more general social interaction between criminal accomplices or between perpetrators and victims that leads to crime after school. Our data highlights the time of crime incidents and we divide these crimes into three periods: school hours (6:00 A.M. to 2:00 P.M.), after school (2:00 P.M. to 10:00 P.M.), and night (10:00 P.M. to 6:00 A.M. the following day). Table **??** shows the results of applying our empirical strategy to the CBG by day panel of crime incidents, split out by time of day. As shown in column (1), in-service days lead to 0.0101 fewer incidents per CBG during school hours. Perhaps more interesting, column (2) shows that crime falls by roughly the same amount, 0.0068 incidents per CBG, during the hours after school. Given the relative mean number of crimes during these respective time periods, our estimates indicates a 5% drop in crime during school hours and a 4% decrease after school hours on in-service days. By night time, the effect of in-service days fades. These effects match the description in Figure **??**. When school is in session, crime increases slightly at the beginning of school and during the day, but the larger increase in crime comes from more incidents in the afternoon hours that make up the end of the school day and the period immediately after school. Appendix Figure ?? shows strong violent crime effects throughout the school day as well as after school, while Appendix Figure ?? shows muted effects for property crimes throughout the school day as well as after school.

5.2 Heterogeneity by Where Students Live and Attend School

If social interactions in school facilitate crime then we should not only see crime fall on teacher in-service days, but we should also see it decrease more dramatically in spaces where students are active. If students do not attend school, they are most likely to be at-home or in other areas near their home. As described above, we use student-level data from the Charlotte-Mecklenburg school system to identify how many and what kind of students live in each neighborhood (CBG) and attend each school in a given school year.[6]

Table ?? demonstrates that on in-service days, crime falls more near schools, particularly those with a large proportion of high risk students. The first column of Table ?? replicates the result that crime falls by 0.026 incidents per CBG per day on in-service days. Columns (2) and (3) split the sample and thus this effect between neighborhoods without and with middle or high schools located in the CBG. Crime still falls somewhat in neighborhoods without schools, dropping by 0.016 incidents or 3%, but crime falls more substantially near schools, decreasing by .091 incidents or 10% in CBGs with schools. Column (4) further divides the sample of CBGs with schools into quartiles by the proportion of high risk students. We see large drops in crime for schools with very high, high, and medium concentrations of high risk students. One of the most interesting results we see is for the bottom quartile, or low crime risk schools, where we see a statistically significant increase of 0.057 incidents. This result is consistent with a story of positive social interaction among lower crime risk juveniles and consistent with the idea of positive peer influences in school that may prevent crimes. These results are robust to the definition of neighborhood; column (5) shows similar results defining all variables according to Census tracts rather than block groups.[7]

[6] The prevalence of high risk students varies significantly across CBGs, averaging 37 but with a standard deviation of 40.

[7] Though there are many more block groups than tracts in Charlotte, the sample size falls

We can visualize the contrast between schools with high risk and low risk students in several ways. Figures **??** and **??** display the contrast between the effect of in-service days on very high risk and low risk schools. Closing school for the day decreases crime during and just after the school day near schools with many high risk students while slightly increasing crime near schools with few high risk students. More simply, Figure **??** displays which CBGs have higher and lower crime rates on in-service days versus other days. This figure also provides the location of schools with very high and low concentration of high crime risk students. The main story from this map is that we see a higher frequency of CBG crime decreases on in-service days for the very high risk schools relative to CBGs with low risk schools.

One other way to think about the effects of student composition in our results is to use a structural break in the student composition across public schools. Our study time period spans a large change in student composition that occurred. Charlotte-Mecklenburg Schools largely redrew school attendance boundaries in summer 2002, and we can test if in-service effects change around 2002. Between the spring 2002 and spring 2003 academic years about one-half of student were assigned to a new school and schools became substantial more segregated based on race and income.[8] Table **??** provides results around this cutoff and shows that negative effects for in-service days grow in magnitude after 2002 even though average crime rates were relatively stable. The end of busing concentrated higher risk youth into particular schools, and larger effects in the post-busing period are consistent with increased potential benefits to minimizing school social interactions on in-service days.

Neighborhoods where many high risk students tend to live also experience a larger reduction in crime on in-service days. Table **??** replicates the analysis of Table **??** using locations where students live instead of where they attend school. Comparing neighborhoods where no students live and those where at least one student lives is not helpful because students live in nearly every CBG; however, comparing neighborhoods with a greater proportion of high risk kids

only slightly because we restrict the sample to locations with schools, and a much larger percentage of tracts (versus CBGs) have a school.

[8] This year represented a major change in school assignment policy due to the end of race-bused busing in Charlotte, NC. See **?** for a rich history of this policy shift and school attendance boundaries in Charlotte, NC

in residence to those with a lesser proportion still proves useful. Again, as a benchmark, crime falls by 0.0261 incidents in the average CBG. As shown in Column (2), neighborhoods with the largest proportion of high risk student residents see crime drop by nearly twice as much, 0.0477 incidents. Neighborhoods with a low proportion of high crime risk students only see crime fall by a statistically insignificant 0.0065 incidents. This more muted effect for lower crime risk neighborhoods may be a result of neighborhood factors that limit the impacts of positive school social interactions.

5.3 Spillovers

We also test whether the effect of in-service days spills into surrounding neighborhoods. Table **??** displays these results. The first column replicates our main finding that crime falls by 0.026 crimes per CBG on in-service days. Column (2) tests whether this effect differs depending on whether there is a school in the CBG, in a different CBG in the same census tract, or nowhere in the tract. As above, we find a much larger drop of 0.084 incidents in CBGs with a school. For CBGs without schools, crime falls by 0.0137 incidents if there is also no school in the rest of the tract and 0.0265 incidents if there is a school in a different CBG in the same tract. The larger and more statistically significant effect for CBGs with nearby schools suggests that in-service effects near schools spill into neighboring CBGs. However, these two coefficients are not statistically different, and we cannot reject a hypothesis of equal spillovers for CBGs with and without schools in the rest of the tract. These results suggest fairly localized crime effects from in-service days with smaller spillover effects into nearby neighborhoods. Column (3) investigates whether in-service effects depend on the risk-level of the student population for schools in neighboring CBGs, but the results show no clear pattern. Altogether, we find some suggestive evidence that having a school in another CBG in the same tract increases the in-service day effect. These results are consistent with a world in which in-service days most strongly decrease crime near schools, and that effect decays as one travels further from the school.

5.4 Police Effectiveness

In principle, contemporaneous changes in policing might also contribute to changes in observed crime rates when schools close for the day. The effect of policing could drive crime either direction. Police could increase patrols to prevent vandalism on in-service days or pull back in anticipation of less crime generated around schools. Either change could affect either actual crime levels or the likelihood that a given crime is reported and recorded in incident data. On the other hand, if in-service days lead to a real change in crime, this could affect the likelihood that the police clear the crime with an arrest. If high crime rates lead to high workloads for police and thus a lower probability of clearing the crime, clearance rates may increase on in-service days. Therefore, if in-service days reduce crimes that tend to be cleared (e.g. violent crimes) more than crimes that are less likely to be cleared (e.g. theft from auto), then clearance rates may decrease on in-service days through a composition effect. A researcher using arrest data would then over or under estimate the effect of closing school on actual crime levels.

To test potential mechanisms involving police effectiveness, we exploit incident-level data on whether the crime was cleared by police. Table **??** shows the results of this model. Column (1) applies our main empirical model as a linear probability model, testing whether the probability that police clear a crime changes on in-service days. The coefficient of -0.0076 indicates that the probability police clear a crime falls by 0.76 percentage points on in-service days. In principle, this result could indicate either that the police simply reduce staffing on in-service days or that in-service days change the composition of crimes. We find evidence for the latter. Column (2) shows that when we add fixed effects for crime types (according to the types shown in the appendix tables) the effect of in-service days on the probability of crime clearance disappears. Columns (3) through (5) demonstrate that splitting the data broadly as violent, property, and other crime is not sufficient. In-service days affect the relative likelihood of particular crimes, which lowers the likelihood that police clear crimes overall. On the other hand, we do not find support for the idea that changes to police staffing on in-service days affects police effectiveness and thus crime.

6 Conclusions

Using short-term disruptions in school attendance due to in-service days, we confirm prior studies that schools provide social interactions that increase crime during and after school on regular school days. Using heterogeneity in both the location of schools as well as students, we show that social interactions related to crime are strongest for both schools and neighborhoods with high concentrations of high crime risk students. Interestingly, we show that crime actually increases on in-service days near schools with high concentrations of low crime risk students, providing support for positive social interactions among low crime risk students.

Altogether, our results suggest that social interactions generate more crime only in schools with many high risk students rather than in all schools. Having school in session may both eliminate some crime through incapacitation effects and generate other crime by encouraging social interactions between potentially collaborating perpetrators or between perpetrators and victims. Our results indicate that in schools with many high risk students, negative social interactions dominate, making the school a place that enhances criminal outcomes. For schools with low crime risk students, positive social interactions decrease criminal activity.

Overall, these results provide evidence that policies that concentrate or dilute social interactions between high crime risk peers will affect the level, location, and timing of crime. Most directly, changes in the school calendar will shift a city's crime map with implications for policing. Our results also speak to specific policies that may leverage social interactions to decrease crime. Consistent with recent papers ((?) & (?)) that show the positive impact of racially and economically diverse school assignment on criminal outcomes, policies aimed at encouraging interaction of high crime-risk students with low crime-risk peers may reduce short term criminal outcomes. These results suggest that mentoring programs which pair up higher crime risk youths with low crime risk mentors may be beneficial and that sports and other school based groups may also help promote group activities with lower crime risk peers. In aggregate, our results highlight strong effects of social interactions among high crime risk students on crime levels, which may speak to the strength of criminal youth peer effects.

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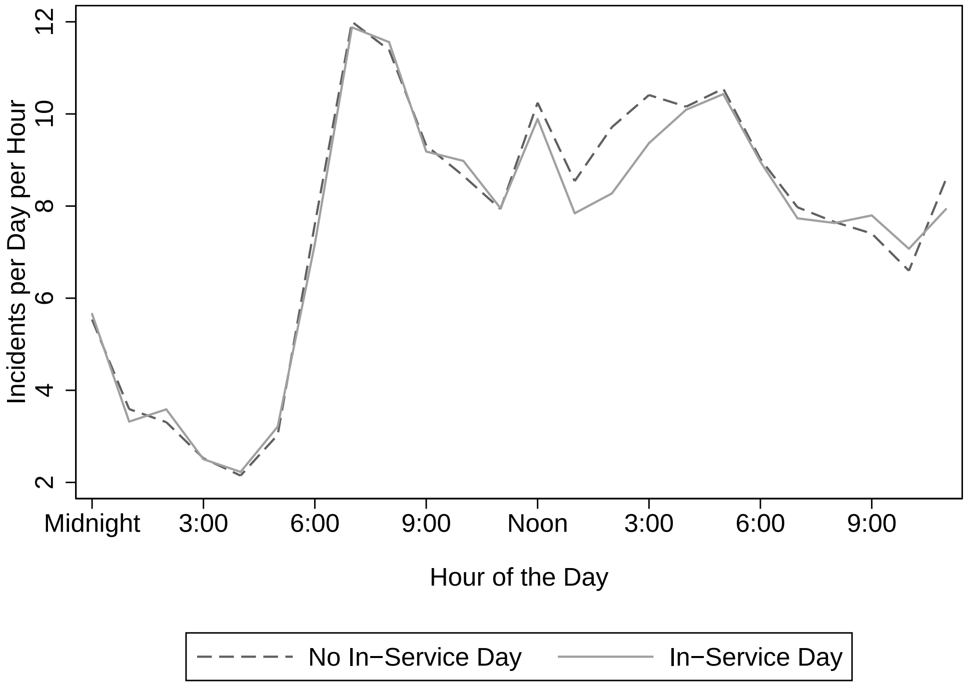
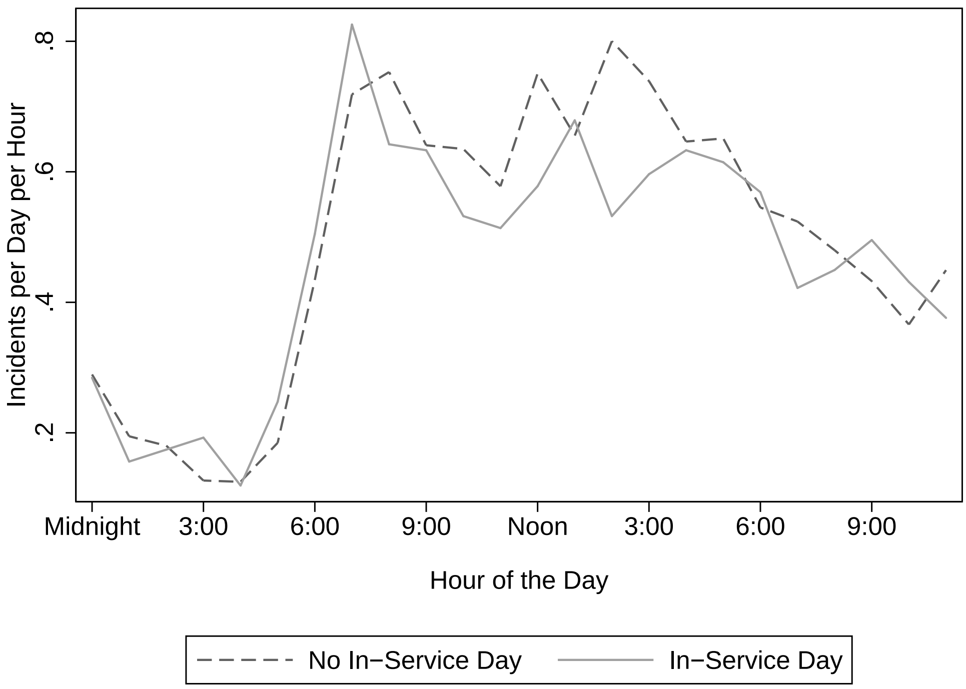
7 Figures and Tables

Figure 1: Incidents by Hour of the Day - Full Sample



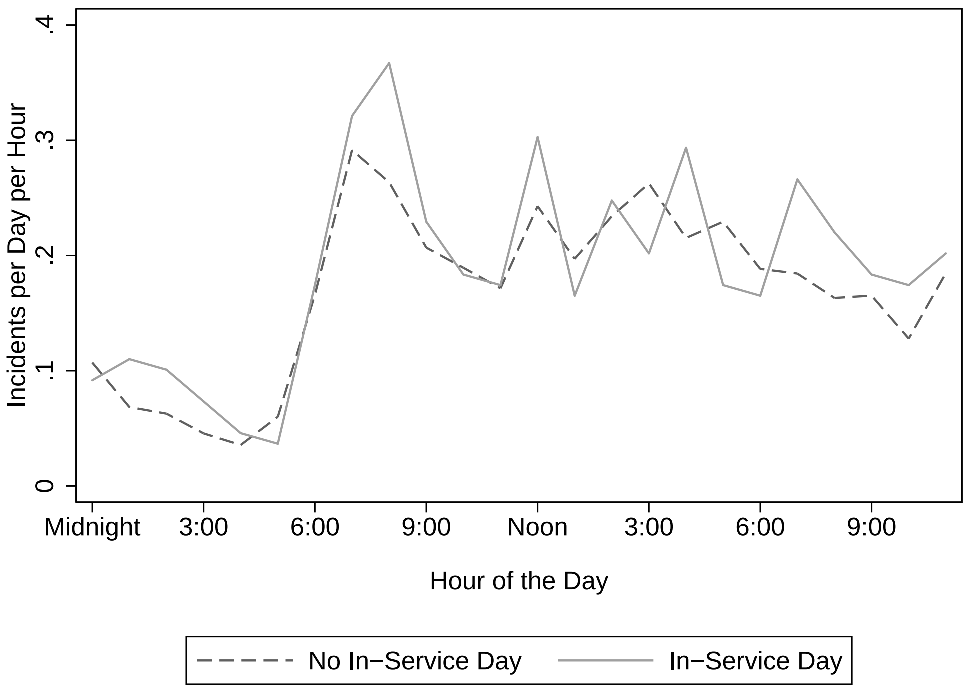
The figure shows average number of crime incidents for the entire county for the 1998-99 through 2010-2011 school years, split out by hour of the day and whether there is an in-service day. The sample excludes weekends, summer break, and national holidays.

Figure 2: Incidents by Hour of the Day - Only CBGs with Very High Risk Schools



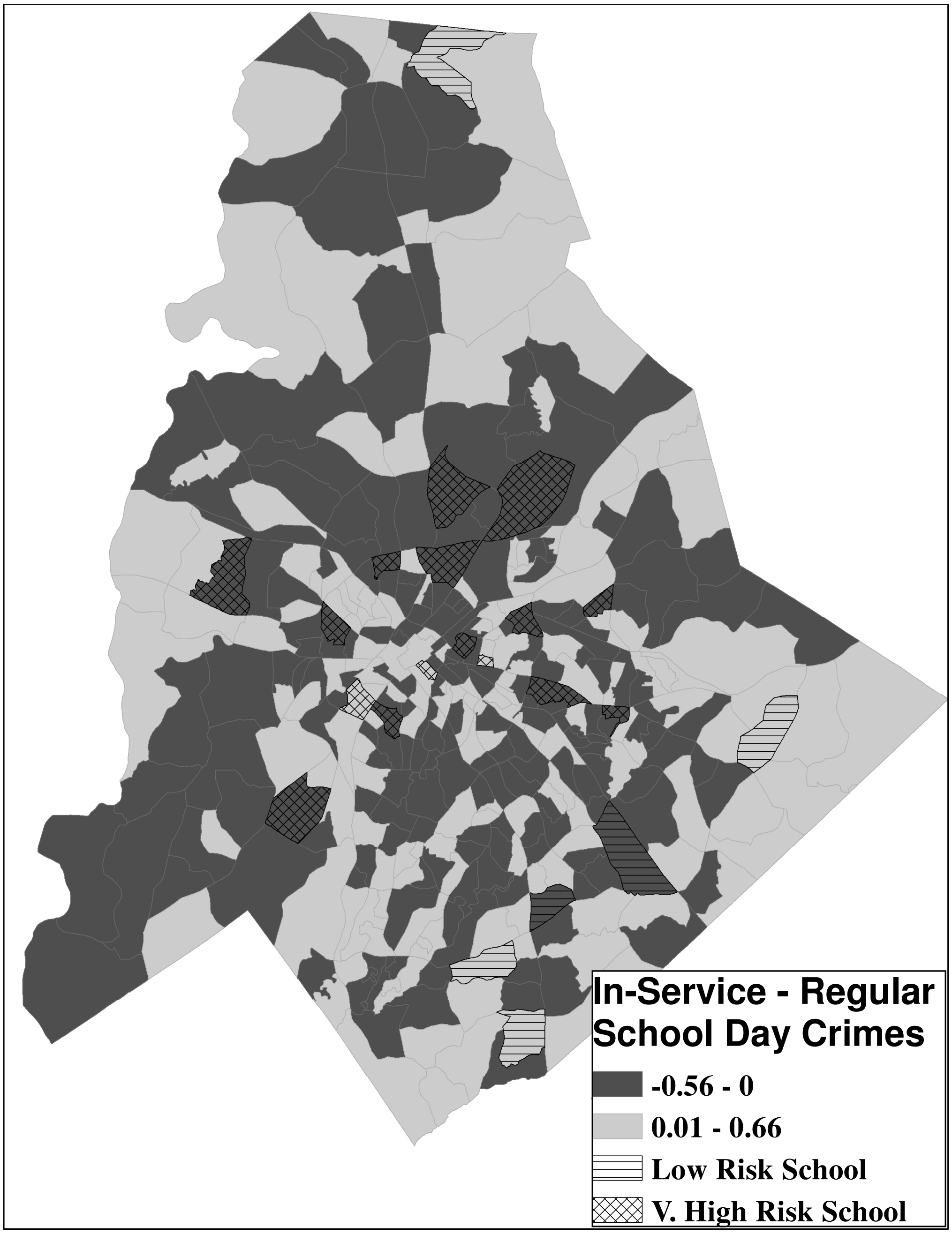
The figure shows average number of crime incidents split out by hour of the day and whether there is an in-service day for the 1998-99 through 2010-2011 school years for Census Block Groups with schools where the proportion of high risk students is in the top quartile. The sample excludes weekends, summer break, and national holidays.

Figure 3: Incidents by Hour of the Day - Only CBGs with Low Risk Schools



The figure shows average number of crime incidents split out by hour of the day and whether there is an in-service day for the 1998-99 through 2010-2011 school years for Census Block Groups with schools where the proportion of high risk students is in the bottom quartile. The sample excludes weekends, summer break, and national holidays.

Figure 4: Areas with Increasing vs. Decreasing Crime on In-Service Days



The figure shows the difference in the average number of crime incidents per day on in-service days versus other days in each CBG. Dark (light) areas indicate decreased (increased) crime on in-service days. The sample excludes weekends, summer break, and national holidays. Very high risk schools are those for which the proportion of high risk students is in the top quartile, while low risk are the bottom quartile of predicted crime risk.

Table 1: Summary Statistics

	In-Service	Not In-Service	Total
Incidents	0.64	0.65	0.65
	(1.09)	(1.11)	(1.11)
−6:00 AM to 2:00 PM	0.20	0.20	0.20
	(0.53)	(0.53)	(0.53)
−2:00 PM to 10:00 PM	0.18	0.18	0.18
	(0.49)	(0.48)	(0.48)
−10:00 PM to 6:00 AM	0.10	0.11	0.11
	(0.35)	(0.37)	(0.37)
–Violent	0.11	0.13	0.13
	(0.37)	(0.39)	(0.39)
–Property	0.41	0.40	0.40
	(0.82)	(0.82)	(0.82)
–Other	0.12	0.13	0.13
	(0.38)	(0.39)	(0.39)
Juvenile Arrests	0.014	0.014	0.014
	(0.12)	(0.12)	(0.12)
–Violent	0.0040	0.0040	0.0040
	(0.065)	(0.065)	(0.065)
–Property	0.0052	0.0046	0.0046
	(0.075)	(0.070)	(0.071)
–Other	0.0051	0.0056	0.0056
	(0.073)	(0.077)	(0.077)
In-Service Day	1	0	0.025
	(0)	(0)	(0.16)
summer	0	0.21	0.20
	(0)	(0.41)	(0.40)
National Holiday	0.15	0.022	0.025
	(0.36)	(0.15)	(0.16)
Saturday or Sunday	0	0.29	0.29
	(0)	(0.46)	(0.45)
Monday or Friday	0.61	0.28	0.29
	(0.49)	(0.45)	(0.45)

The sample is a panel of Census Block Groups and days for the 1998-99 through 2010-2011 school years. Means are shown with standard deviations in parentheses. Crime incidents are counts of all incidents recorded by the Charlotte-Mecklenburg Police Dept. Arrests are arrests of juveniles age 16-18 by the Mecklenburg County Sheriff's Dept. Days are categorized as in-service or summer according to the Charlotte-Mecklenburg school calendar. National holidays are classified as days for which the SP 500 has no listing.

Table 2: In-Service Days and Citywide Crime

	(1) All	(2) All	(3) Violent	(4) Property	(5) Other
Incidents	-10.1^{***}	-9.73^{***}	-3.09^{***}	-2.13	-4.50^{***}
	(2.67)	(2.72)	(0.85)	(2.03)	(0.82)
Mean of Dep. Var.	243.2	243.2	46.6	149.2	47.3
R-Squared	0.70	0.70	0.46	0.65	0.68
Juvenile Arrests	-0.86^{***}	-0.98^{***}	-0.49^{***}	0.11	-0.60^{***}
	(0.28)	(0.28)	(0.14)	(0.18)	(0.17)
Mean of Dep. Var.	5.26	5.26	1.47	1.70	2.09
R-Squared	0.36	0.37	0.27	0.20	0.28
Summer and Holiday Controls	N	Y	Y	Y	Y
Day of Week FE	Y	Y	Y	Y	Y
Week X Year FE	Y	Y	Y	Y	Y
Observations	4,748	4,748	4,748	4,748	4,748

The sample is a daily time series for the entire city of Charlotte for the 1998-99 through 2010-2011 school years. For the first panel, the outcome is the number of crime incidents and for the second panel the outcome is the number of juvenile arrests. The listed coefficient is for an in-service dummy variable. Robust standard errors are in parentheses. Summer and holiday controls include dummies for the summer break period, listed school holidays, listed school leave days, and national holidays. Days are categorized as in-service, summer, leave or school holiday according to the Charlotte-Mecklenburg school calendar. National holidays are classified as days for which the SP 500 has no listing.

Table 3: In-Service Days and Neighborhood Crime

	(1) All	(2) All	(3) Violent	(4) Property	(5) Other
Incidents x 100	-2.71^{***}	-2.61^{***}	-0.83^{***}	-0.57	-1.21^{***}
	(0.66)	(0.68)	(0.21)	(0.50)	(0.20)
Mean of Dep. Var.	65.4	65.4	12.5	40.1	12.7
R-Squared	0.01	0.34	0.11	0.25	0.10
Juvenile Arrests x 100	-0.23^{***}	-0.26^{***}	-0.13^{***}	0.029	-0.16^{***}
	(0.070)	(0.071)	(0.036)	(0.045)	(0.043)
Mean of Dep. Var.	1.41	1.41	0.40	0.46	0.56
R-Squared	0.00	0.01	0.01	0.00	0.01
Summer and Holiday Controls	N	Y	Y	Y	Y
Day of Week FE	Y	Y	Y	Y	Y
Week X Year FE	Y	Y	Y	Y	Y
CBG FE	N	Y	Y	Y	Y
Observations	1,766,256	1,766,256	1,766,256	1,766,256	1,766,256

The sample is a panel of Census Block Groups and days for the 1998-99 through 2010-2011 school years. For the first panel, the outcome is the number of crime incidents (x100) and for the second panel the outcome is the number of juvenile arrests (x100). The listed coefficient is for an in-service dummy variable. Standard errors clustered by date are in parentheses. Summer and holiday controls include dummies for the summer break period, listed school holidays, listed school leave days, and national holidays. Days are categorized as in-service, summer, leave or school holiday according to the Charlotte-Mecklenburg school calendar. National holidays are classified as days for which the SP 500 has no listing.

Table 4: Placebo Test - 1 Week Lag and Lead of In-Service

	(1) All	(2) All	(3) Violent	(4) Property	(5) Other
In-Service Day 1 Week Ago	0.87	0.74	0.24	0.46	0.041
	(0.71)	(0.71)	(0.20)	(0.51)	(0.23)
Mean of Dep. Var.	65.4	65.4	12.5	40.1	12.7
R-Squared	0.01	0.34	0.11	0.25	0.10
In-Service Day 1 Week in Future	−0.76	−0.77	−0.22	−0.72*	0.17
	(0.57)	(0.56)	(0.20)	(0.40)	(0.21)
Mean of Dep. Var.	65.4	65.4	12.5	40.1	12.7
R-Squared	0.01	0.34	0.11	0.25	0.10
Summer and Holiday Controls	N	Y	Y	Y	Y
Day of Week FE	Y	Y	Y	Y	Y
Week X Year FE	Y	Y	Y	Y	Y
CBG FE	N	Y	Y	Y	Y
Observations	1,763,652	1,763,652	1,763,652	1,763,652	1,763,652

The sample is a panel of Census Block Groups and days for the 1998-99 through 2010-2011 school years. For both panels, the outcome is the number of crime incidents. The listed coefficients are the coefficients on a one-week lag and one week lead of the in-service dummy variable, run in separate models. Standard errors clustered by date are in parentheses. Summer and holiday controls include dummies for the summer break period, listed school holidays, listed school leave days, and national holidays. Days are categorized as in-service, summer, leave or school holiday according to the Charlotte-Mecklenburg school calendar. National holidays are classified as days for which the SP 500 has no listing.

Table 5: Effects on Incidents by Time of Day

	(1) 6:00 AM to 2:00 PM	(2) 2:00 PM to 10:00 PM	(3) 10:00 PM to 6:00 AM
In-Service Day	-1.01^{***}	-0.68^{***}	-0.25
	(0.33)	(0.26)	(0.21)
P-value (= Late Night Effect)	0.02	0.15	
Mean of Dep. Var.	20.0	18.2	10.6
R-Squared	0.13	0.14	0.10
N	1,766,256	1,766,256	1,766,256

The sample is a panel of Census Block Groups and days for the 1998-99 through 2010-2011 school years. All models include day of week FE, week-year FE, CBG FE, and dummies for the summer break period, listed school holidays, listed school leave days, and national holidays. Days are categorized as in-service, summer, leave or school holiday according to the Charlotte-Mecklenburg school calendar. National holidays are classified as days for which the SP 500 has no listing. Standard errors clustered by date. The final row uses seemingly unrelated regressions to test the hypothesis that the coefficient on the treatment dummy is equal to the same coefficient in column (3).

Table 6: Heterogeneity by Where Students Attend School - Incidents x 100

	(1) All	(2) No Schools	(3) Schools	(4) Schools	(5) Schools
In-Service Day	-2.61^{***}	-1.64^{**}	-9.06^{***}		
	(0.68)	(0.66)	(1.63)		
In-Service X Low Risk				5.66^{***}	5.76^{*}
				(2.17)	(3.43)
In-Service X Medium Risk				-6.99^{**}	-13.2^{***}
				(2.87)	(4.53)
In-Service X High Risk				-15.7^{***}	-23.8^{***}
				(2.84)	(4.88)
In-Service X Very High Risk				-17.6^{***}	-17.9^{***}
				(3.47)	(5.26)
P-value (Med Risk = Low Risk)				0.00	0.00
P-value (High Risk = Low Risk)				0.00	0.00
P-value (Very High Risk = Low Risk)				0.00	0.00
Mean of Dep. Var.	65.4	61.5	90.1	90.1	196.7
R-Squared	0.34	0.33	0.34	0.35	0.54
N	1,766,256	1,528,500	237,756	237,756	208,174

The full sample in column (1) is a panel of Census Block Groups and days for the 1998-99 through 2010-2011 school years. Columns (2) and (3) split the sample into CBGs with or without a middle or high school. Column (4) splits the schools sample into quartiles according to the proportion of high risk students attending school in the CBG. The first four columns all include day of week FE, week-year FE, CBG FE, and dummies for the summer break period, listed school holidays, listed school leave days, and national holidays. Days are categorized as in-service, summer, leave or school holiday according to the Charlotte-Mecklenburg school calendar. National holidays are classified as days for which the SP 500 has no listing. The fourth column also includes risk group dummies and interacts the day of week FE, week-year FE, and summer-holiday controls with the risk group dummies. Column (5) replicates Column (4) but with a panel of census tracts rather than CBGs and all variables defined by census tract. Standard errors clustered by date.

Table 7: Heterogeneity by Where Students Live - Incidents x 100

	(1) Students	(2) Students	(3) Students
In-Service Day	-2.61^{***}		
	(0.68)		
In-Service X Low Risk		-0.65	-1.42
		(0.60)	(1.66)
In-Service X Medium Risk		-1.34	1.12
		(0.98)	(2.41)
In-Service X High Risk		-3.68^{***}	-8.01^{***}
		(1.32)	(2.59)
In-Service X Very High Risk		-4.77^{***}	-6.74^{**}
		(1.22)	(2.84)
P-value (Med Risk = Low Risk)		0.50	0.44
P-value (High Risk = Low Risk)		0.02	0.03
P-value (Very High Risk = Low Risk)		0.00	0.10
Mean of Dep. Var.	65.4	65.4	169.6
R-Squared	0.34	0.34	0.46
N	1,760,411	1,760,411	678,598

The sample in columns (1) and (2) is a panel of Census Block Groups and days for the 1998-99 through 2010-2011 school years restricted to observations with students living in the CBG during that school year. This restriction removes 16 out of 4,836 CBG-years. Column (2) splits the schools sample into quartiles according to the proportion of high risk students living school in the CBG. The first two columns include day of week FE, week-year FE, CBG FE, and dummies for the summer break period, listed school holidays, listed school leave days, and national holidays. Days are categorized as in-service, summer, leave or school holiday according to the Charlotte-Mecklenburg school calendar. National holidays are classified as days for which the SP 500 has no listing. The fourth column also includes risk group dummies and interacts the day of week FE, week-year FE, and summer-holiday controls with the risk group dummies. Column (3) replicates Column (2) but with a panel of census tracts rather than CBGs and all variables defined by census tract. Standard errors clustered by date.

Table 8: Spillovers from Schools in the Same Tract - Incidents x 100

	(1) All	(2) All	(3) All
In-Service Day	-2.61^{***}		
	(0.68)		
In-Service X School in CBG		-8.41^{***}	-8.35^{***}
		(1.58)	(1.59)
In-Service X No School in Tract		-1.37^{*}	-1.27^{*}
		(0.71)	(0.72)
In-Service X School in Rest of Tract		-2.65^{***}	
		(0.95)	
In-Service X Low Risk in Rest of Tract			-0.65
			(1.57)
In-Service X Medium Risk in Rest of Tract			-3.07^{*}
			(1.76)
In-Service X High Risk in Rest of Tract			-4.16^{**}
			(1.78)
In-Service X Very High Risk in Rest of Tract			-1.70
			(2.09)
P-value (School in Tract = School in CBG)		0.00	
P-value (School in Tract = No School in Tract)		0.18	
P-value (Med Risk = Low Risk)			0.27
P-value (High Risk = Low Risk)			0.13
P-value (Very High Risk = Low Risk)			0.70
Mean of Dep. Var.	65.4	65.4	65.4
R-Squared	0.34	0.34	0.34
N	1,766,256	1,766,256	1,766,256

The sample in all columns is a panel of Census Block Groups and days for the 1998-99 through 2010-2011 school years. The first column includes day of week FE, week-year FE, CBG FE, and dummies for the summer break period, listed school holidays, listed school leave days, and national holidays. Days are categorized as in-service, summer, leave or school holiday according to the Charlotte-Mecklenburg school calendar. National holidays are classified as days for which the SP 500 has no listing. In column (2), we also include interactions of the day of week and week-year FE with all possible combinations of the 'school in CBG', 'school in tract', and 'no schools' variables. We also include the summer and holiday controls interacted with each of the three school variables. Likewise, in column (3) we interact the day of week and week-year FE with all possible combinations of the 'school in CBG' and tract school risk indicators. We also include the summer and holiday controls interacted with each of the school group indicators. Standard errors clustered by date.

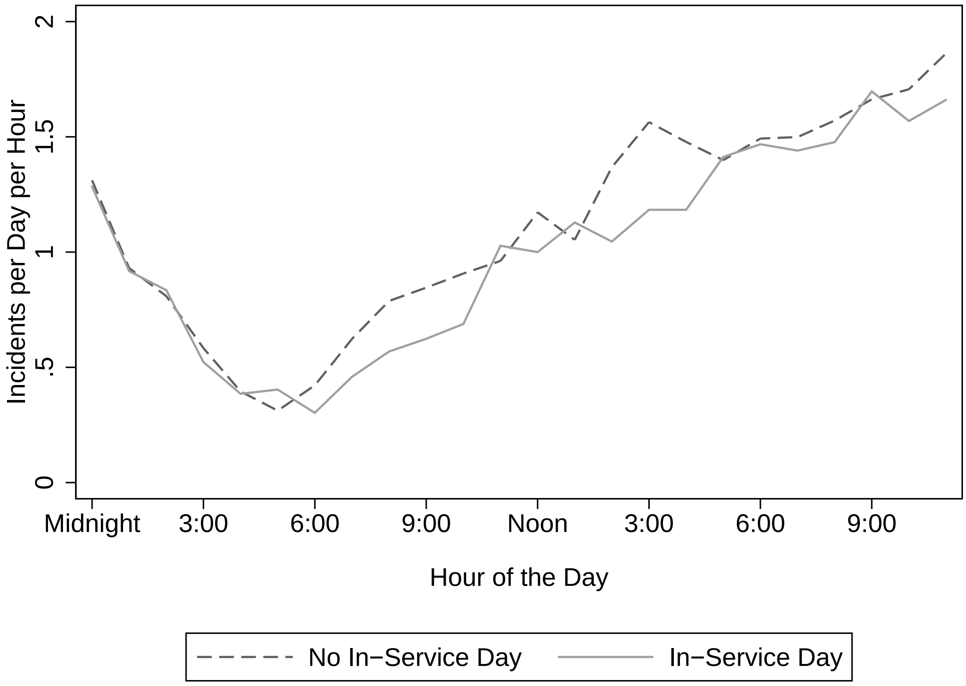
Table 9: Clearance Probability - Individual Incident Data

	(1) All	(2) All	(3) Violent	(4) Property	(5) Other
In-Service Day	-0.0076^{**}	-0.00013	-0.024^{***}	0.0056^{**}	-0.0033
	(0.0032)	(0.0027)	(0.0075)	(0.0028)	(0.0069)
Crime Type FE	N	Y	N	N	N
P-value (1) = (2)	0.00				
Mean of Dep. Var.	0.30	0.30	0.56	0.14	0.55
R-Squared	0.03	0.25	0.05	0.04	0.11
N	1,165,088	1,165,088	221,343	708,571	235,174

The sample is individual incident-level data for all incidents for the 1998-99 through 2010-2011 school years. All models include day of week FE, week-year FE, CBG FE, and dummies for the summer break period, listed school holidays, listed school leave days, and national holidays. Days are categorized as in-service, summer, leave or school holiday according to the Charlotte-Mecklenburg school calendar. National holidays are classified as days for which the SP 500 has no listing. Standard errors are clustered by date. The final row uses seemingly unrelated regressions to test the hypothesis that the coefficient on the treatment dummy is the same in columns (1) and (2).

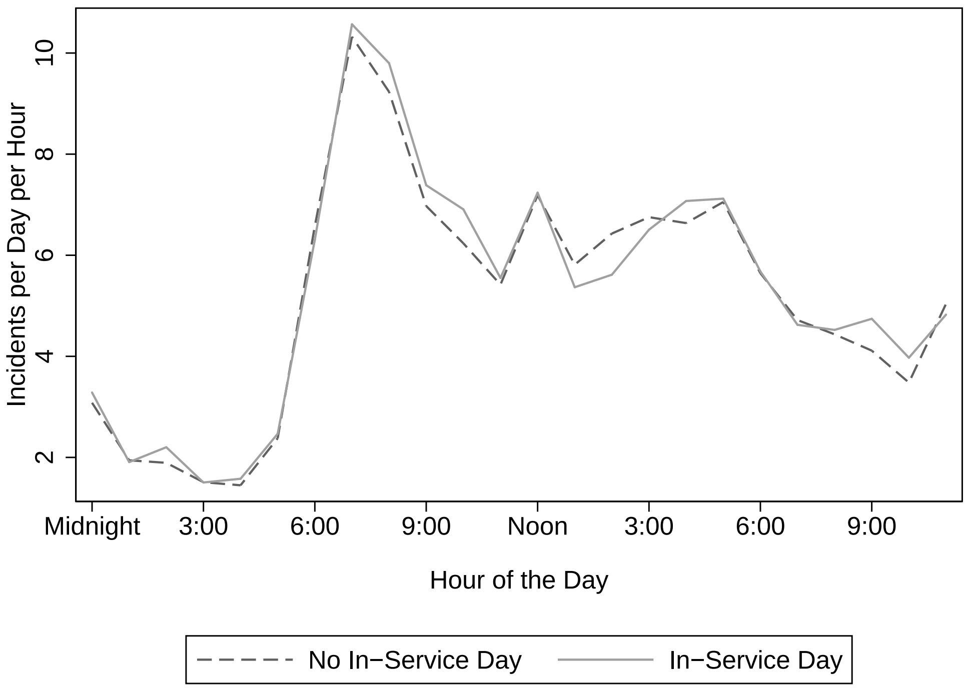
Appendix - *For Online Publication*

Figure A1: Violent Incidents by Hour of the Day - Full Sample



The figure shows average number of violent crime incidents for the entire county for the 1998-99 through 2010-2011 school years, split out by hour of the day and whether there is an in-service day. The sample excludes weekends, summer break, and national holidays.

Figure A2: Property Incidents by Hour of the Day - Full Sample



The figure shows average number of property crime incidents for the entire county for the 1998-99 through 2010-2011 school years, split out by hour of the day and whether there is an in-service day. The sample excludes weekends, summer break, and national holidays.

Figure A3: Violent Incidents by Hour of the Day - Only CBGs with Very High Risk Schools

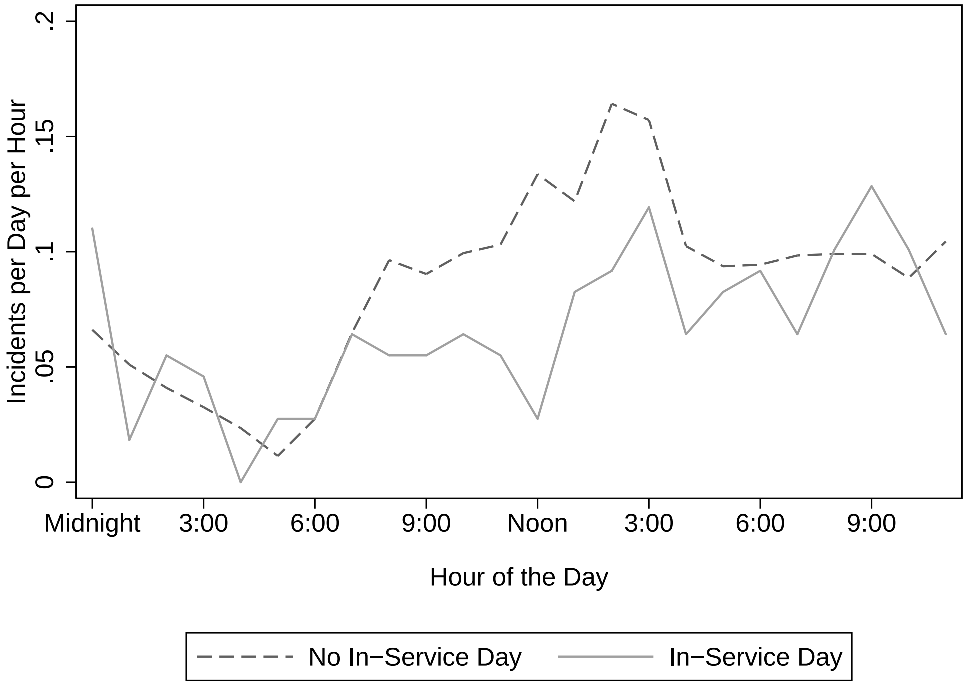


Figure A4: Violent Incidents by Hour of the Day - Only CBGs with Low Risk Schools

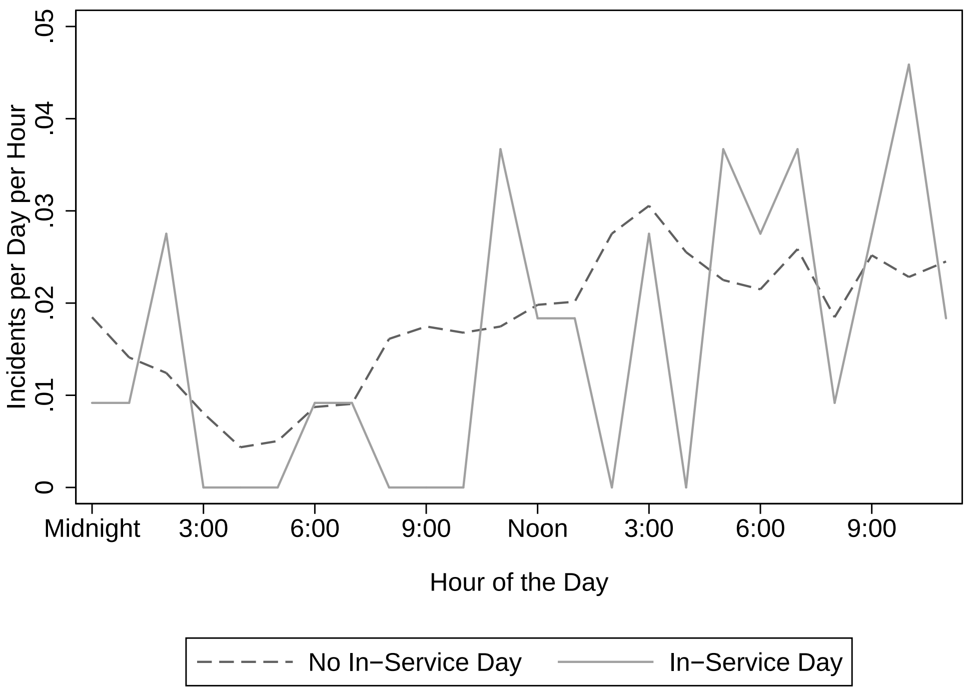


Figure A5: Property Incidents by Hour of the Day - Only CBGs with Very High Risk Schools

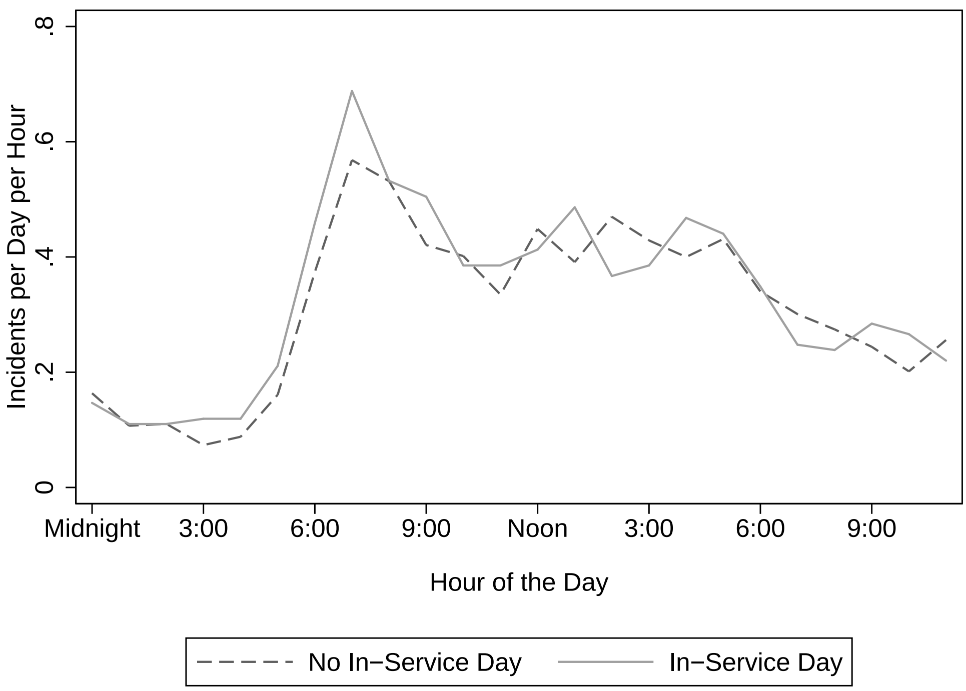


Figure A6: Property Incidents by Hour of the Day - Only CBGs with Low Risk Schools

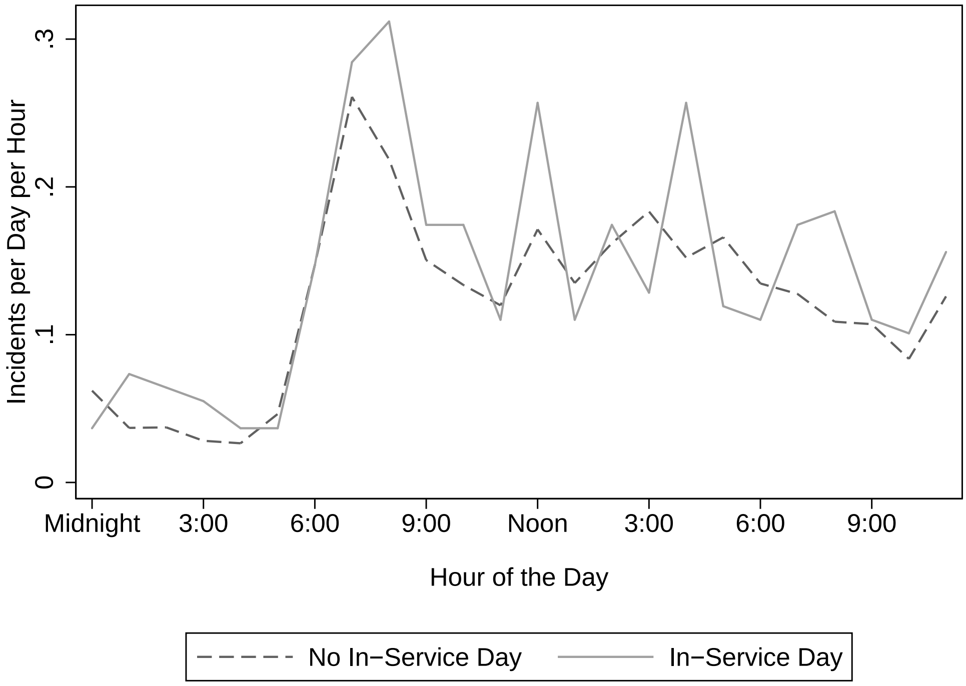


Table A1: Incidents - by Crime Type

	Arson	Assault	Auto Theft	Burglary	Drugs	Forgery/Fraud	Hit and Run	Kidnapping	Larceny
In-Service Day	0.012	-0.96^{***}	0.18	-0.53^{***}	0.0029	-0.32^{***}	0.012	0.0018	−0.23
	(0.022)	(0.17)	(0.12)	(0.20)	(0.066)	(0.12)	(0.031)	(0.0023)	(0.26)
Mean of Dep. Var.	0.21	9.96	3.65	7.81	0.77	2.45	0.49	0.00	18.00
R-Squared	0.00	0.09	0.04	0.05	0.04	0.04	0.03	0.00	0.18
N	1,766,256	1,766,256	1,766,256	1,766,256	1,766,256	1,766,256	1,766,256	1,766,256	1,766,256

	Murder	Other	Robbery	Sex Offense	Stolen Property	Theft from Auto	Vandalism	Weapons
In-Service Day	0.0052	-1.20^{***}	0.081	-0.13^{**}	−0.033	0.025	0.36^{***}	-0.079^{***}
	(0.012)	(0.19)	(0.070)	(0.056)	(0.029)	(0.072)	(0.13)	(0.022)
Mean of Dep. Var.	0.06	11.74	1.97	0.54	0.19	1.55	5.75	0.21
R-Squared	0.00	0.10	0.03	0.01	0.00	0.06	0.04	0.01
N	1,766,256	1,766,256	1,766,256	1,766,256	1,766,256	1,766,256	1,766,256	1,766,256

Table A2: Heterogeneity by Where Students Attend School Over Time - Incidents x 100

	(1) All, 99-02	(2) All, 03-11	(3) Schools, 99-02	(4) Schools, 03-11
In-Service Day	−1.71	−2.98***		
	(1.17)	(0.84)		
In-Service X Low Risk			10.4*	4.41*
			(5.91)	(2.28)
In-Service X Medium Risk			−12.3**	−3.34
			(5.35)	(3.27)
In-Service X High Risk			−17.0***	−14.9***
			(4.75)	(3.55)
In-Service X Very High Risk			−15.7**	−18.0***
			(6.79)	(4.02)
P-value (Med Risk = Low Risk)			0.00	0.04
P-value (High Risk = Low Risk)			0.00	0.00
P-value (Very High Risk = Low Risk)			0.00	0.00
Mean of Dep. Var.	63.8	66.1	98.2	87.3
R-Squared	0.33	0.35	0.36	0.36
N	543,492	1,222,764	62,093	175,663

The first three columns split the full panel of Census Block Groups and days for the 1998-99 through 2010-2011 school years into equal groups by school year. Columns (4) to (6) make the same split but only for CBGs with a middle or high school. For the latter columns, risk groups are quartiles of the proportion of high risk students attending school in the CBG. Summer and holiday controls include dummies for the summer break period, listed school holidays, listed school leave days, and national holidays. Days are categorized as in-service, summer, leave or school holiday according to the Charlotte-Mecklenburg school calendar. National holidays are classified as days for which the SP 500 has no listing. Standard errors clustered by date.