

# School and Crime

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April 22, 2022

## Abstract

Criminal activity is seasonal, peaking in the summer and declining through the winter. We provide the first evidence that arrests of children and reported crimes involving children follow a different pattern: peaking in the fall and spring and declining in the summer. Using a regression discontinuity design surrounding school start and end dates for over 2,000 school districts in the U.S., we show that this pattern is caused by the school environment—children aged 10–17 are roughly twice as likely to be involved in a reported crime during the beginning of the school year relative to the weeks before school begins. This sharp increase is driven by student-on-student crimes occurring between 7am–8pm, within and nearby to school. We use the timing of these patterns and a seasonal adjustment to argue that within our sample of law enforcement agencies—covering around 50% of the U.S. population—the school environment increases reported crime among 10–17-year-olds by 41% annually and increases arrests of 10–17 year-olds by 27% annually. We find similar percent increases in arrests and reported crimes across different demographic groups. However, due to different baseline levels of reported crimes, the school environment exacerbates inequality in absolute terms, increasing the Black-white (and male-female) gap in reported juvenile crime rates by 41%. We use a nationally representative victimization survey to argue that our results are not explained by reporting bias.

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# 1 Introduction

Criminal activity rates peak for teenagers before declining sharply through age 20 (Shulman et al., 2013). This age-crime curve and the authors' analysis of the NLSY97 show that most adults who engage with the criminal justice system are first exposed to that system as children. While many papers document this relationship between age and criminal activity, there is little work understanding the causal predictors of early-age criminal offenses.<sup>1</sup>. In this paper, we use the exact dates of reported criminal offenses to show that school plays an important role in driving increases in reported and realized criminal activity among children. School-based law enforcement interactions often represent children's first experience with the criminal justice system, so policy responses to these cases have the potential to affect the lifelong relationship between children and the carceral state.

A large literature documents seasonal patterns in crime rates. Block (1984) documents seasonality in crime by crime type, highlighting 180 years of academic work in a similar vein dating back to Quetelet (1842). Quetelet, a Belgian social scientist, showed that person-on-person crime peaked in the summer and dropped in the winter. Recent evidence from a large panel of U.S. cities finds modern-day empirical support for these patterns—with overall criminal activity peaking in the summer McDowall et al. (2012). We use incident-level data from the National Incident-Based Reporting System (NIBRS) to trace out seasonality in criminal activity by age, confirming the general finding that overall criminal activity peaks in the summer.<sup>2</sup> But we then focus on children aged 10–17 and show that this group does not follow the overall pattern: criminal activity involving children as either offenders, victims, or arrestees peaks during the school year and falls during the summer. In a paper that closely parallels our work, Hansen and Lang (2011) show that suicide rates jump in the months when school is in session.

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<sup>1</sup>For one exception, see Davison et al. (2021).

<sup>2</sup>See Appendix Figure A.1 for all reported crimes (Panel A) and all arrests (Panel B) using 2017-2019 NIBRS data.

To show that this descriptive fact reflects a causal relationship, we use school start dates and end dates from over 2,000 large school districts linked to nearby law enforcement agencies and a regression discontinuity design to show that this reverse seasonality is largely caused by the start and end of the school year, which leads to a dramatic increase in rates of reported crime. We draw on the work of Fitzpatrick et al. (2020), who use a similar method to show that the start of the school year leads to a sharp increase in reports of child maltreatment. We also draw from Jacob and Lefgren (2003), who use teacher in service days to study short-term breaks from school and find that being in school causes lower property crime but higher violent crime. Our work relates to Luallen (2006) who show that teacher strikes lead to higher rates of property crime but lower rates of violent crime; Akee et al. (2014), who show that time away from school decreases crime; Fischer and Argyle (2018), who shows that there is higher crime (particularly property crime) when schools change to a four-day school week; and Bacher-Hicks et al. (2022), who show that in-person school closures resulting from the Covid-19 pandemic decreased school bullying and cyber-bullying.

We use data from the National Crime Victimization Survey to show that our results are not driven by changes in reporting bias—we find the same patterns described above when we analyze monthly rates of victimization self-reported by a nationally-representative sample of respondents in The National Crime Victimization Survey (NCVS). This result is mirrored by prior work from Carbone-Lopez and Lauritsen (2013) who are the first we know of to descriptively document seasonality in victimization rates among children (albeit at a monthly level), also using the NCVS. We additionally use the NCVS to show similar patterns for offenders.

We further explore heterogeneity in this bimodal seasonal pattern of crime for 10–17-year-olds and show that the increase in crime during the school year is driven by crime reported during school hours (7am to 8pm) on weekdays, crimes involving acquaintances, drug crimes, and assaults (but not property crimes), and crimes reported as occurring in

school. In fact, we see the opposite (and standard) seasonal pattern of crime peaking in the summer for crimes involving 10–17-year-olds for crimes that are reported as having occurred outside of school.

To better understand the exact geography of these crimes, we focus on two places: Austin and New York City, which provide additional information about reported crimes. In Austin, TX, there are two distinct law enforcement agencies that report crimes separately: the Austin Police Department and the Austin Independent School District Police Department. We show that the Austin Police Department shows the standard unimodal seasonality in reported crimes involving 10–17-year-olds—with the number of crimes peaking in the summer—while the Austin police department that operates only within schools shows strong patterns of seasonality consistent with the bimodal patterns of seasonality described above. Relatedly, in New York City we observe the latitude and longitude of reported crimes, and we show that the seasonal patterns described above are explained by reported crimes within 0.25 miles of a school; and we see the strongest patterns for crimes reported from significantly closer to the school. We see little evidence of seasonal patterns aligned with the school year for crimes involving 10–17-year-olds that are reported more than 0.25 miles away from a school.

We conclude our paper by quantifying the fraction of ‘excess’ crime among 10–17-year-olds that is caused by the academic calendar. We granularly control for general seasonal patterns in reported crime during non-school-hours and we calculate the residual crime among each age group in our sample. We find no residual (‘excess’) crime for the older cohorts (aged 19+) during the school year and school day, but we find strong evidence of school-related seasonality among 10–17-year-olds. On the average weekday during the school year, 10–17-year-olds are involved in around 600 additional crimes and 150 additional arrests in our sample of law enforcement agencies reported to NIBRS. Calibrated to our sample of law enforcement agencies reporting to NIBRS, we argue that the school environment causes a 41% increase in reported crimes and a 27% increase in

reported arrests among 10–17-year-olds annually. We then focus on demographic subgroups and argue that the school environment (separately) causes a 41% increase in reported crimes for male, female, Black, and white children. These 41% increases magnify gaps in reported crimes by demographic group, increasing annual Black-white and male-female gaps in reported crime rates by 41%.

## 2 Empirical strategy

### 2.1 Data and Sample Selection

Our primary data source for reported crime is the National Incident-Based Reporting System, or NIBRS, for the years 2017-2019.<sup>3</sup> NIBRS is a crime reporting system used by many, but not all, police departments across the United States. In 2019, agencies reporting to NIBRS covered around half of the U.S. population, documenting criminal incidents in areas with 147 million U.S. residents and 8,500 law enforcement agencies.<sup>4</sup> NIBRS contains information on the exact date and hour of each incident; the type of incident; the age, race, and sex of the victims and offenders; and the relationships between the victims and offenders. Not all variables are observed for every incident. In addition, we observe if the incident resulted in an arrest or citation.<sup>5</sup> Each incident corresponds to a law enforcement agency (LEA), and we observe the location of each agency using the Law Enforcement Agency Identification Crosswalk, which provides us with the agency's approximate longitude and latitude.<sup>6</sup> For our analysis involving location of crime, we

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<sup>3</sup>We obtain these data from Kaplan (2021).

<sup>4</sup>See <https://www.fbi.gov/news/pressrel/press-releases/fbi-releases-2019-nibrs-crime-data> for more details.

<sup>5</sup>In particular, we observe if the incident resulted in the offender being 1) “taken into custody (based on warrant and/or previous incident report)”; 2) given an “on-view arrest (taken into custody without a warrant or previous incident report)”; or 3) “summoned/cited (not taken into custody).” We include categories 1 and 2 when constructing our arrest variable.

<sup>6</sup>We use the 2012 version of the crosswalk, downloaded via United States. Bureau of Justice Statistics. Law Enforcement Agency Identifiers Crosswalk, United States, 2012. Inter-university Consortium for Political and Social Research [distributor], 2018-09-18. <https://doi.org/10.3886/ICPSR35158.v2>

rely on NIBRS data for the years 2010-2016.<sup>7</sup>

We conduct our analysis at the weekly level. To do so, we assign NIBRS incident date and, where applicable, school starting (or ending) date into weeks of the year such that the first Monday of the year is in the first week and the next-occurring Sunday is the final day of the first week. Days before the first Monday are considered week 0. The second Monday of the year begins the second week, and so on. In general, we omit weeks 0, 52, and 53. We aggregate the number of reported crimes or arrests to the weekly level. NIBRS reports information for more than one type of offense and for multiple offenders and victims. Throughout, we consider only the first-listed offense type and information for only the first offender and victim.

For much of our analysis, we use only the NIBRS data described above, referred to as the ‘main sample.’ However, we also explore a regression discontinuity design (RDD), using school start and end dates to demonstrate a causal link between reported crime and school. We refer to this sample, described below, as the ‘RDD sample.’

To implement our RDD, we first gather school calendar information for the 2019–2020 school year from [publicholidays.com](http://publicholidays.com).<sup>8</sup> We observe school calendar information for 11,245 districts, and for nearly every district we observe both the first and last days of school (as well as Thanksgiving, Christmas, and spring breaks).<sup>9</sup> We obtain similar results using older NIBRS data and an entirely different source for school district start dates.<sup>10</sup>

We link school districts to the NIBRS data using geographical information. We first assign each school district a latitude-longitude pair obtained from the National Center

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<sup>7</sup>We download, extract, and standardize the annual extracts from <https://www.icpsr.umich.edu/web/NACJD/series/128>. We rely on ICPSR series 33601, 34603, 35036, 36121, 36421, 36851, and 37066 in this paper.

<sup>8</sup>We also have data for 2020–2021 and 2021–2022, but focus on 2019–2020 to avoid confounding our estimates with the Covid-19 pandemic.

<sup>9</sup>We also observe holidays such as fall break, Easter break, and midwinter break, though these are less common.

<sup>10</sup>These results are unreported. The alternate source for school start dates is Pew Research, which collected these data for a 2019 article. See DeSilver (2019). Before sample restrictions, the Pew data provides school start dates for 509 school districts across the U.S.: the ten largest school districts for each state (the exceptions being Hawaii and Washington, D.C., which have only one school district) as well as several additional large districts.

for Education Statistics (NCES) Education Demographic and Geographic Estimates using the Public School District file from 2019–2020<sup>11</sup>. To do so, we clean the school district names for both the school district and NCES datasets and then match on state and district name.<sup>12</sup> This gives us the county, state, and geocoordinates for each school district. We then assign to each school district the closest LEA (from NIBRS), the distance being calculated using the sets of geographical coordinates and corrected for the curvature of the earth (i.e., using the WGS ellipsoid).

Because the coverage of NIBRS is not comprehensive (or for other reasons), some school districts are clearly not assigned to the correct LEA. We therefore require that the LEA and school district 1) be in the same county and 2) be no more than 20 miles apart.

Multiple school districts are sometimes mapped to one LEA. This can happen if there are multiple large school districts in a city served by only one agency. In these cases, we keep only LEAs that map to school districts for which all school start (end, etc.) dates occur during the same week. Our final RDD sample for the start of school (before any additional sample restrictions, such as requiring a valid age of offender) consists of 1,384 LEAs representing 2,451 school districts. For the end of school, there are 1,269 LEAs representing 2,004 school districts.

In order to provide the cleanest estimate, in our RDD analysis, we focus only on 2019 NIBRS linked to the 2019-2020 school calendar information. We do not consider 2020 due to the Covid-19 pandemic. 2019–2020 is the earliest available school year with information for the school calendar. This means that the school start date is measured more accurately than the school end date because the incidents occurred during 2019, but the school calendar represents the school end date for 2020.<sup>13</sup> However, it is our sense that

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<sup>11</sup>See <https://nces.ed.gov/programs/edge/Geographic/SchoolLocations>.

<sup>12</sup>To clean both sets of school district names, we convert the names to be lower case and then remove a number of things that may cause the strings to differ, including numbers and words such as “school”, “district”, and “county”. We also drop school district observations in NCES that appear multiple times after cleaning.

<sup>13</sup>It is unclear if publicholidays.com updated the 2019-2020 school calendar to reflect any changes in the wake of the Covid-19 pandemic, but the results are very sharp, leading us to believe that they did not.

school calendars do not change much year-to-year, and our results for school end date are very sharp, suggesting this is not a cause for concern.

In addition the NIBRS data, we also analyze data from the 1992-2020 National Crime Victimization Survey (NCVS), a nationally representative survey measuring the number and types of victims of crimes in the U.S. By comparing seasonality for children's criminal behavior in NIBRS and the NCVS, we can explore whether the patterns we focus on are explained by changes in the reporting of crimes surrounding the school year. We find no evidence that our results (for crimes involving victims) are explained by reporting bias.

One shortcoming of NIBRS is that it does not include sub-LEA geocoded information. While NIBRS does include information on crime location (home, business, etc.), we do not observe the latitude and longitude of the reported crime. To fill this gap, we use New York City (NYC) incident-level crime data<sup>14</sup> These data include the age range of the offender and victim, the date of incident, and (approximate) geocoded location of incident. We link each under 18-year-old offender incident to the nearest school, where the school location is obtained from the NCES Education Demographic and Geographic Estimates using the Public School file and Private School file from 2019–2020.<sup>15</sup> We use this distance variable to consider how crime changes over the year for reported crimes various distances away from the nearest school.

## 2.2 Specification

Our main results rely on two types of analyses—first, because the results we present below are visually sharp, we focus on raw counts of reported crimes committed by offenders in different demographic groups over different time periods. These plots of raw outcomes provide convincing evidence of the empirical patterns we study in this paper.

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<sup>14</sup>We considered 41 cities that had crime data and found only two—New York City and Cincinnati—that had age (range) of offender, date of incident, and geocoded location. Three others have age (range) of victim, date of incident, and geocoded location. For this draft, we focus on New York City.

<sup>15</sup>See <https://nces.ed.gov/programs/edge/Geographic/SchoolLocations>.

Second, to precisely estimate our statistical claims, we rely on a regression discontinuity design to estimate the effect of children attending school on crime. We present plots in the style of a regression discontinuity design where we stack the set of crimes in even-time surrounding the week when schools first began (or finished) each calendar years. These plots show even sharper empirical results, but are largely consistent with the raw data. In the future we plan to present estimates derived from a standard regression discontinuity design with the inclusion of covariates such as weather, and a focus on algorithmically-produced optimal bandwidth procedures.

### 3 Results

We begin by presenting several graphs that show seasonal patterns of reported crime in the 2017–2019 NIBRS data. First, we plot the total number of reported crimes by week in Figure 1. We limit the sample to offenders 10–17 years old in Panels A and B, to offenders 19–24 years old<sup>16</sup> in Panels C and D, and to offenders 25–30 years old in Panels E and F. The left Panels (A, C, and E) show all reported incidents and the right Panels (B, D, and F) subset to incidents resulting in the arrest of an offender. Across each of these figures, we see an increase in reported crime and arrests between the start of the year and roughly week 20 (occurring in May), and a decrease in reported crime from around week 40 (in September) to the end of the year. However, these patterns for each age group sharply diverge between roughly weeks 20 and 40 (September and May) for 10–17 year-olds when compared to the other age groups. In particular, we see a dramatic decrease in reported crime and arrests for 10–17-year-olds beginning in September, and a sharp decline in reported crimes and arrests beginning at the end of May.<sup>17</sup> We also consider victim (as opposed to offender) age in Appendix Figure A.2 and find similar results. Taken together,

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<sup>16</sup>We do not consider age 18 because it is an in-between group, as only some people remain in school at this age. However, the figures look similar if we include 18-year-olds in the 10–17 group.

<sup>17</sup>For arrests, we rely on the reported age of offender. But the correlation between age of offender and age of arrestee is 0.98 across the entire sample, so these plots look similar when we rely on arrestee age.

these findings suggest that school, which typically recesses during the summer, may play a role in the sharp divergence between the calendar week and reported crimes and arrests for 10–17-year-olds relative to other groups.

### 3.1 RDD Analysis

We proceed to consider patterns in reported crime by week relative to estimated school district start date in Figure 2. These figures are limited to the RDD sample described above, with the panels arranged as in Figure 1. We do not run a regression or control for seasonality—instead, we simply line up each school district such that the week of the school districts start is at  $t = 0$  and we sum reported crimes (or arrests) for each relative calendar week. Patterns for all incidents for 19–24 and 25–30-year-olds are similar to each other (Panels C and E), while the pattern for 10–17 year-olds looks dramatically different. We observe a large increase (an almost doubling) of reported crimes for 10–17 year-olds beginning around each school district’s start date (Panel A), with similar results when considering only arrests (Panel B). For both total counts of reported criminal incidents in NIBRS and total arrests, we observe an even larger decrease in reported crime between 9 and 12 weeks before the school start date, suggesting that the end of school is also an important driver of changes in reported crime involving children.<sup>18</sup>

The results in Figure 3 demonstrate a sharp decrease in reported crime around the last day of school for offenders aged 10–17, both for the total count of criminal incidents in NIBRS and for arrests—reported crimes almost halve within a few weeks of school ending. This discontinuity does not exist for the older age groups. Taken together, the large discontinuities around both the beginning and end of school provide compelling evidence that school causes an increase in reported crime.

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<sup>18</sup>See Appendix Figure A.3 for RDDs on other school breaks such as fall break and spring break.

### 3.2 Is This Just Reporting Bias?

In Figure 4, we use the National Crime Victimization Survey (aggregated from 1992–2020) to show that the previous results (based on NIBRS data) are not solely explained by changes in reporting patterns caused by increased scrutiny of crimes committed during the school year. The NCVS microdata contains information from a survey of U.S. households, identifying the members of each household who were victimized by crimes, and the month when that victimization occurred. Between August and September, when most schools begin their school year, we see a large spike in reports of victimization among 10–17-year-olds. And we see a similar drop in reported victimization rates as we move from May to June—lining up with the end of school. We see the opposite summer pattern in criminal victimization for 19–24 and 25–30-year-olds (in Panels B and C): victimization rates spike for these age groups in the summer. This is consistent with the literature on the seasonality of crime. Results are mirrored for reported offender age in the NCVS, based on the recollection of the victims (Panels B, D, and F).

### 3.3 Heterogeneity

We now return to the NIBRS dataset to better understand the above results by exploring various dimensions of heterogeneity: age of offender; hour of the day; whether the reported crime was committed in or outside of school; weekends/weekdays; age of offender/age of victim combinations; type of offense; relationship of offender to victim; reported sex of offender; and reported race of offender. We present all results in the raw data, without relying on the smaller RDD subsample that contains school calendar information, and we focus on all incidents (as opposed to only arrests). Unless otherwise specified, we consider offenders aged 10–17.

We begin by looking at heterogeneity by offender age in Figure 5, where each panel represents an age, from 11 to 18. We find the same pattern for each age from 10–17, but

the pattern disappears—or becomes highly muted—at age 18, when many students are no longer enrolled in high school. Focusing on the trough-to-peak jump around the beginning of school for each age, the percent increase in reported crimes is largest for the youngest ages and smallest for the older ages. There is a more than doubling of reported crimes involving 10–13-year-old offenders, but only a 25% increase in the reported offenses committed by offenders who are 17 years old.

We next consider the hour of the day the incident occurred. Figure 6 splits the data into the 24 hours of the day. The number of incidents between 1am and 6am peaks in the summer, consistent with general patterns of reported criminal behavior involving only adults, but we see that pattern flip starting at 7am, at which point reported crimes involving 10–17-year-olds dip in the summer and peaks when the school year begins and ends. The summer dip continues until roughly 8pm, at which point most students are at home from school, and the pattern then reverses, returning to the standard summer peak in reported crimes we see for crimes involving adults.<sup>19</sup> This is consistent with the increase in reported crime happening during and immediately after the typical school day, when students are returning home. At first glance, it may seem surprising that the pattern persists several hours after many schools finish. But remember that students may still be involved in activities at school after the school day ends, such as after-school sports, and they may also experience less supervision if their parents are still at work for several hours after the school day ends. In addition, the percent increase from trough to peak is much larger at, say, 3–4pm than it is from 6–7pm.

In Figure 7, we recreate the plots of Figure 1, but split the sample by whether the reported crime occurred out-of-school or in-school, where we include college/university in our definition of school.<sup>20</sup> The first thing to note is that reported crimes committed in school are orders of magnitude more common for 10–17-year-olds, who are typically all

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<sup>19</sup>Note that the number of reported crimes from 12-12:59am appear to suffer from reporting bias. It appears that if the time of day was unknown that is may have been assigned to this time range.

<sup>20</sup>Recall that this analysis uses NIBRS years 2010-2016 as opposed to 2017-2019.

enrolled in school, and reported crimes committed in school are much less common for 19–24 and 25–30-year-olds, who are less likely to be enrolled. The results are striking: all age groups have a large summer decrease in reported crime for those committed at school and the typical summer-peaking seasonal pattern for reported crimes not committed at school. These results show that crimes committed at school explain the entirety of the summer drop (and fall increase) in reported crime for children.

In Figure 8, we consider reported crimes occurring on weekdays (Panels A, C, and E) and weekends (Panels B, D, and F). The typical summer-peaking seasonal pattern occurs for older age groups for both weekdays and weekends. In contrast, we find the summer dip for 10–17-year-olds across both types of days. However, the percent increase from summer to the beginning of the fall is much larger for weekdays versus weekends.

We proceed to consider the interaction of offender and victim age in Figure 9. In particular, we replicate Figure 1, but split the sample by age of offender and age of victim. We focus on two age ranges: 10–17-years-olds; and offenders or victims aged 19 and older. We observe the typical summer-peaking seasonal pattern for reported crimes involving adult offenders and adult victims (Panel D), and a strong summer trough for child offenders and child victims (Panel A). There is a much smaller summer trough for reported crimes involving child offenders and adult victims (Panel B) and we see even less evidence of school-related seasonality for reported crimes involving adult offenders and child victims (Panel C), although these estimates are much noisier. We further probe offender and victim age by presenting offender and victim age pairs for offenders aged 12–14 in Appendix Figure A.4 and offenders aged 15–17 in Appendix Figure A.5. Each column corresponds to a given offender age. Each row corresponds to victim ages that are a given age range away from offender age, where the first row is for victims three years younger than the offender and the final row is for victims that are two years older than the offender age. In all cases, reported crime is most common when the offender and victim are the same age, and tends to decrease with the age difference. With some exceptions,

we typically observe the lower-crime-in-the-summer pattern when the age difference is two years or less. It is likely that our results are at least in part explained by students who are in the same grade as each other, or at least in the same school. While we do not have data on which grades tend to be in which school buildings across our districts, we expect that results would be strongest for students who are in the same physical school as each other, in accordance with prior evidence on the importance of peers and network effects in reported criminal activity (for example, Billings et al. (2019)).

In Figures 10 and 11, we show that these patterns are explained by several offense categories. After classifying UCR codes into ten groups of crimes, we show that the beginning of the school year causes a sharp uptick in reported drug crimes and simple assaults, as well as reported non-violent crimes like intimidation and weapons law violations. We see either a weaker pattern (meaning a small percentage difference between trough and peak) or do not see this pattern at all for killings; theft; sexual assault; and property damage or vandalism.

We next split the sample by the relationship of the offender to the victim in Figure 12. Reported crimes in which the offender is an acquaintance to the victim are both most common and have the strongest summer trough pattern in terms of percent increases in reported crimes (along with the uncommon ‘the victim is the offender’ category).<sup>21</sup> This pattern also appears to varying degrees for the other groups, being strongest among friends and romantic relationships and much weaker among family members and strangers.

In Figures 13 and 14, we examine these trends separately for males and females, as well as by the race categories law enforcement agencies classify offenders and victims into.<sup>22</sup> We see the same general patterns across sex-based and race-based groups. Surprisingly, for offenders and victims among all categories—males, females, and each racial

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<sup>21</sup>Victim is offender can occur in instances such as brawls, where an individual both attacks and is attacked.

<sup>22</sup>The race categories we use are White, Black, and Other Race, into which we group American Indian, Alaskan Native, Asian, Native Hawaiian, and Pacific Islander.

classification—we find roughly the same proportional increase in reported crime, approximately 50%, surrounding the start of the school year. This indicates that the school environment has a proportional **percent** increase in reported crimes involving each group. As we point out in the last subsection of our results, these proportional percent increases in reported crimes for different demographic groups are percent increases from different levels, entailing that the school environment causes sharp increases in the Black-white gap and male-female gap in reported crimes and arrests.

### 3.4 Case Study: School-based LEAs

To explore the mechanisms underlying these effects, we now consider the phenomenon of school districts that have their own law enforcement agency. As a case study, we consider the city of Austin, Texas and the Austin Independent School District (ISD), which have distinct law enforcement agencies that operate separately and report separately to NIBRS. In Figure 15 Panel A, we plot the reported crimes by week for 10–17-year-old offenders in the Austin ISD, which provides law enforcement support to the public school system. We see a sharp drop in reported crime during the summer weeks, with reported crimes during these weeks being zero or close to it. Around calendar week 35, there is a sharp uptick in reported crime. This is in contrast to the Austin police department (Panel B), which has a relatively uniform rate of reported crime involving 10–17-year-old offenders over the year (though there is a dip at the end of the summer). In Panel C, we show reported crime for a broader sample of LEAs that include the word “school,” “schools,” “isd”, or “i.s.d.” in their title. We see the same pattern as in Panel A. For comparison, in Panel D, we plot weekly reported crime for colleges and university LEAs (that include the word “college” or “university” in their title; age is unrestricted). We see a similar pattern, though the baseline level of reported crime in summer months is much greater than for school LEAs likely because many LEAs at colleges and universities exist separately from town-level or city-level LEAs, but that reporting behavior and separation of responsibility

is less common for public K-12 school systems.<sup>23</sup>

### 3.5 Distance to Nearest School - New York City

We now turn our attention to New York City, which records the latitude and longitude of its reported crimes in incident-level microdata. We associate each reported crime for offenders 17-years-old and younger to the nearest school in New York City, and we present weekly reported crime by distance. In Figure 16, we find a strong summer dip in reported crime—a more than halving—for reported crimes within 0.05 miles of the nearest school (Panel A). We observe a similar, but greatly dampened pattern for reported crimes within 0.05 and 0.1 and between 0.1 and 0.25 miles from the nearest school (Panels B and C). The effect has disappeared (or is very small and noisy) further than 0.25 miles from the nearest school.

In Figure 17, we show that reported crimes for offenders 17 and younger occurring within 0.1 miles from the nearest school show a stronger pattern for public schools (Panel A) than for private schools (Panel B). The pattern is similar in terms of percent change from trough to peak across types of school when we split our sample into schools with many reported crimes (Panel C) and schools with few reported crimes (Panel D). In other words, there is no clear pattern where the schools that have the highest levels of reported crime also see the largest evidence of seasonality in reported crime nearby to the school.

### 3.6 Excess Crime Calculation

In the previous section, we presented evidence that the school environment causes an increase in arrests and reported crimes among 10–17-year-olds. But we have done little to quantify the magnitude of these effects. To approach this question systematically, we focus on the 2019 NIBRS dataset. Within this data, we first calculate an ‘expected’ number of reported crimes and arrests based on seasonality and demographics. Our pro-

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<sup>23</sup>Colleges and universities also tend to have more students enrolled during the summer.

cedure for this is as follows. We construct daily counts of reported crimes and arrests for cells defined by the interaction of calendar day (January 1st, 2019 through December 31st, 2019), hour-of-the-day (midnight to 1am,.. through 11pm to midnight), and age of offender (ages range in this estimation sample from 10 through 39). As an example, one of our cells is the number of reported crimes committed on January 1st, 2019, between the hours of midnight and 1am, by 10-year-olds. We then estimate the following regression at the cell-level, after **subsetting to** cells reported outside of the school calendar and school hours (cells from July or cells outside of July for crimes reported between 8pm and 6am):

$$Y_{a,t,h} = \alpha_{a,t} + \delta_{a,dow(t),h} + \epsilon_i$$

where  $Y_{a,t,h}$  is a count of one of two outcomes—reported crimes or reported arrests in NIBRS—measured for offenders of age  $a$  on calendar day  $t$  during hour-of-the-day  $h$ .  $\alpha_{a,t}$  represents age -by- calendar day fixed effects, and  $\delta_{a,dow(t),h}$  represents day-of-the-week -by- hour-of-the-day -by- age fixed effects. This regression produces a set of seasonal and demographic-based adjustments that we can then use to residualize our counts of arrests and reported crimes at the cell-level throughout the year.

We then take the residualized outcome  $\Delta_{a,t,h} = Y_{a,t,h} - \hat{Y}_{a,t,h}$  and we plot the average residual count of reported crimes or arrests by calendar day and age.<sup>24</sup> Put another way, we are residualizing out both daily seasonality of reported crime, which we allow to vary by age and which we estimate using evening and early morning hours (estimated using  $\alpha_{a,t}$ ), and hourly seasonality of crime, which we allow to vary by day-of-the-week and age, and which we estimate using reported variation in criminal activity throughout the day in the month of July.

In Figure 18 we now plot these residuals, summed across all cells within a calendar date ( $\bar{\Delta}_{a,t,\cdot}$ ). The top panel shows the residuals for weekdays, and the bottom panel shows

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<sup>24</sup>It is important to remember that our  $\hat{Y}_{a,t,h}$  is constructed using the fixed effects from the above equation, estimated only on cells from July and from outside-of-July that are also outside of school hours.

residuals for weekends. In both panels, for each age group we peg the daily residual to be zero on July 1st. Here we see a clear pattern. For non-school-age offenders, the average daily value of these residuals is approximately zero. In other words, the patterns of seasonality for non-school-age offenders during school hours of the year is well-predicted by the patterns of seasonality that we estimate outside of the school year. But, for school-aged children (10–17-year-olds), we see a different pattern. The patterns of seasonality outside the school day do not do a good job of explaining the amount of reported crime during the school day. Instead, during the school year we see elevated counts of reported crime relative to what we would predict based purely on our seasonality estimates. As a placebo test, we can perform the same exercise for weekends (bottom panel), plotting the average residual for each weekend. Here, we no longer see as clear of a pattern. While there are slightly higher average residuals for 10–17-year-olds, perhaps reflecting the increased interactions of students with peers on weekends during the school year (see Panel B of Figure 8, we see similar patterns for 19–24 year-olds.

To quantify the magnitude of these ‘excess’ reported crimes for 10–17-year-olds, on the average weekday, we see 426 excess reported crimes in our 2019 NIBRS data, relative to what we would expect from non-school-hour patterns of seasonality. As a comparison group, we can look at 19–24-year-olds, who are on average reported as having committed 51 additional crimes on a weekday, relative to what we might expect from non-school-hour seasonality patterns. So, to perform a simple back-of-the-envelope calculation, we estimate that the school environment is responsible for  $426 - 51 = 375$  excess reported crimes per weekday, or an excess  $375 \times 261 = 97,875$  reported crimes each year.<sup>25</sup> This is 29% of all 341,910 crimes reported to NIBRS involving 10–17-year-old offenders in 2019. Or, said another way, this calculation implies that the school environment increases reported crimes with 10–17-year-old offenders by  $\frac{97,875}{341,910 - 97,875} = 41\%$ .<sup>26</sup>

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<sup>25</sup>Note that there were 261 weekdays in 2019.

<sup>26</sup>When comparing 10–17-year-olds to 19–24-year-olds, we did not attempt to adjust for the fact that there are generally more incidents involving 19–24-year-old offenders than there are involving 10–17-year-old offenders. This should not affect our ‘comparison’ group significantly, but it could mean that our estimates

We can perform the same exercise for arrests (see Figure 19) to see if these results are driven by less-consequential or more-consequential reported crimes. And here, we find smaller but similar effects. On the average weekday, we see 98 excess reported arrests, relative to what we would expect from non-school-hour patterns of seasonality. As a comparison group, we can look at 19–24-year-olds, who are on average reported as having 25 additional arrests on a weekday, relative to what we might expect from non-school-hour seasonality patterns. This implies that in 2019, the school environment is responsible for  $98 - 25 = 73$  excess reported arrests per weekday, or an excess  $73 \times 261 = 19,053$  reported crimes each year. This is 21% of all 90,099 arrests reported to NIBRS involving 10–17-year-old offenders in 2019. In other words, we argue that the school environment increases arrests among 10–17-year-olds by  $\frac{19,053}{90,099 - 19,053} = 27\%$ .

As a final analysis, we now separately consider how this excess crime measure varies by the reported race and sex of offenders. Here, we find remarkably similar percent increases in crime for each group of offenders. Using the same method reported previously, in Figure 20, we show our daily residual (excess) reported crime on weekdays for male offenders (Panel A), female offenders (panel B), Black offenders (panel C), and White offenders (panel D). Here we see patterns consistent with the results from the prior two paragraphs. In all cases, we see excess reported crime for 10–17-year-olds relative to what we would expect to see from seasonal patterns in crime outside of school hours. In Figure 21, we plot the same residuals but on weekends, and we see no clear pattern.

To quantitatively estimate the number of excess reported crimes due to the school environment, we can now perform the same back-of-the-envelope calculation described above, but separately for male, female, Black, and White offenders. The equation for this calculation, which we apply to each demographic group, is to calculate excess crime as a fraction of total annual crime for a given demographic group as

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are slightly conservative. Another possible ‘control’ group could be the weekend residual excess crime for 10–17-year-olds, from which we would derive similar estimates.

$$\frac{(Excess\ crimes\ per\ weekday_{age\ 10\ to\ 17} - Excess\ crimes\ per\ weekday_{age\ 19\ to\ 24}) \times (261\ weekdays)}{Annual\ crimes_{age\ 10\ to\ 17}}$$

Relying on this formula, we arrive at the following estimates:

Excess crime for all **White** 10–17-year-old offenders is  $\frac{(246.81 - 26.73) * 261}{195,517} = 29.4\%$ .

Excess crime for all **Black** 10–17-year-old offenders is  $\frac{(154.34 - 15.05) * 261}{124,733} = 29.2\%$ .

Excess crime for all **male** 10–17-year-old offenders is  $\frac{(310.48 - 39.77) * 261}{246,515} = 28.7\%$ .

Excess crime for all **female** 10–17-year-old offenders is  $\frac{(114.33 - 10.21) * 261}{93,294} = 29.4\%$ .

In other words, we find that the school environment causes 29% of all crime involving 10–17-year-olds. Using the same logic as we use for the full set of crimes, this means that for each demographic group described above, the school environment is causing a  $\frac{0.29}{1-0.29} = 41\%$  increase in annual reported crimes. And this is separately true for white, Black, male, and female offenders. This may seem somewhat equitable on its face. Whatever is happening during the school day—whether it is related to law enforcement agencies embedded in school systems, differential monitoring of potential crimes, or an increase in reported crimes because school creates additional opportunities for children to interact with peers. But this 41% increase comes from different levels, so the school environment significantly magnifies any preexisting inequities in the amount of race-based or sex-based reported crime rates (or, based on a similar analysis, arrest rates).

To see why this is the case, consider a world with two groups, A and B. In Group A, there are 100 reported crimes with child offenders per 1,000 children annually. In Group B, there are 10 reported crimes with child offenders per 1,000 children annually. This means that there is an A-B gap of 90 reported crimes per 1,000 kids annually. If an intervention increases the number of reported crimes per 1,000 children by 41% for each of Group A and Group B, then in the new state of the world, Group A will report 141 crimes per 1,000 children and Group B will report 14.1 crimes per 1,000 children. So the new A-B gap in

reported crime rates is  $141 - 14.1 = 126.9$  reported crimes per 1,000 children. In other words, the gap has increased by 41%.<sup>27</sup>

The reason we do not calculate the change in the Black-white and male-female reported crime rates directly here is because the denominator is not easy to calculate. NI-BRS data covers around half of the U.S. population, but students in schools do not need to attend schools within the same LEA as their place of residence, although they often do. But, applying the fact described above, we can say that the school environment increased both the male-female and Black-white gaps in reported crime rates by around 41%. To put more specific numbers on this fact, the Office of Juvenile Justice and Delinquency Prevention reports that in 2019, Black 10–17-year-old offenders were involved in 4.2 reported crimes per 1,000 children, and white 10–17-year-old offenders were involved in 1.7 reported crimes per 1,000 children, implying a 2.5/thousand gap in reported crimes.<sup>28</sup> We estimate that the school environment increased the gap from  $\frac{2.5}{1.41} = 1.71$  crimes per thousand children to its current 2.5 crimes per thousand children.

## 4 Conclusion

In this paper, we document a sharp increase in arrests and reported criminal activity involving children as the school year starts, and a sharp decline in both measures as the school year ends. We use a regression discontinuity design to show that this pattern is the result of a causal relationship—as students begin to attend school in the end of summer and early fall, crime rates among children spike. We further find that this pattern is driven by arrests and reported crimes committed during school hours. We use data from a victimization survey to show that these patterns are not explained by changes in crime

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<sup>27</sup>This is seen more generally in a world where group A has X reported crimes per 1,000 children and group B has Y reported crimes per 1,000 children. If an intervention increases reported crime rates by Z%, then the A-B gap in reported crimes increases from  $X - Y$  to  $(1 + Z)X - (1 + Z)Y = (1 + Z)(X - Y)$

<sup>28</sup>These rates are published in the OJJDP Statistical Briefing Book. Arrest rates by offense and race, 2019 (rates are per 100,000 in age group). Available here: [https://www.ojjdp.gov/ojstatbb/crime/ucr.asp?table\\_in=2](https://www.ojjdp.gov/ojstatbb/crime/ucr.asp?table_in=2). Released on November 16, 2020.

reporting patterns during the school year. We argue that the school environment increases reported crime rates among 10–17-year-olds by 41%, and also increases the Black-white gap in reported crimes by 41%. In ongoing work, we hope to further explore the causes of these patterns, spatial heterogeneity in these patterns, and the factors that may ameliorate these patterns.

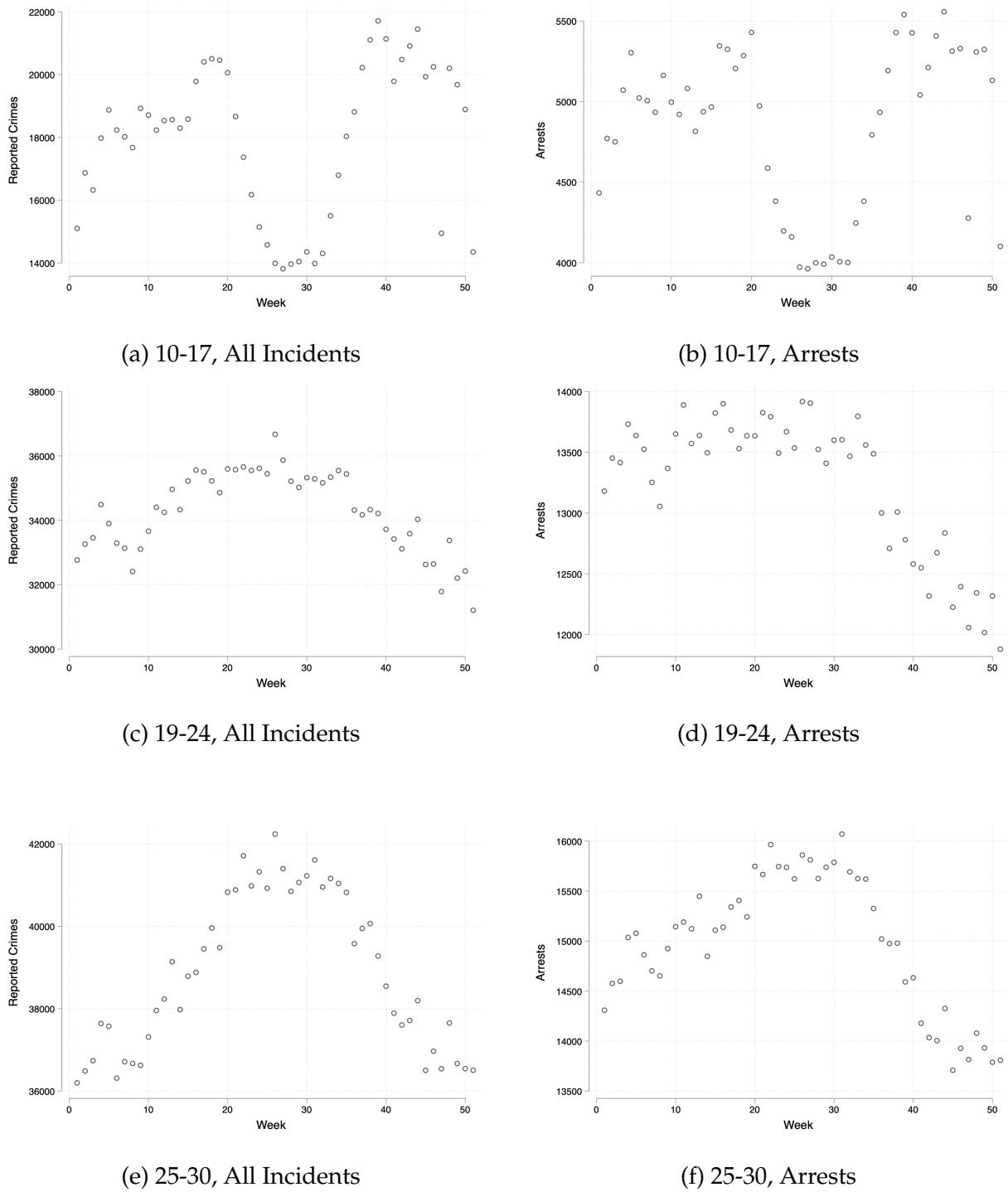
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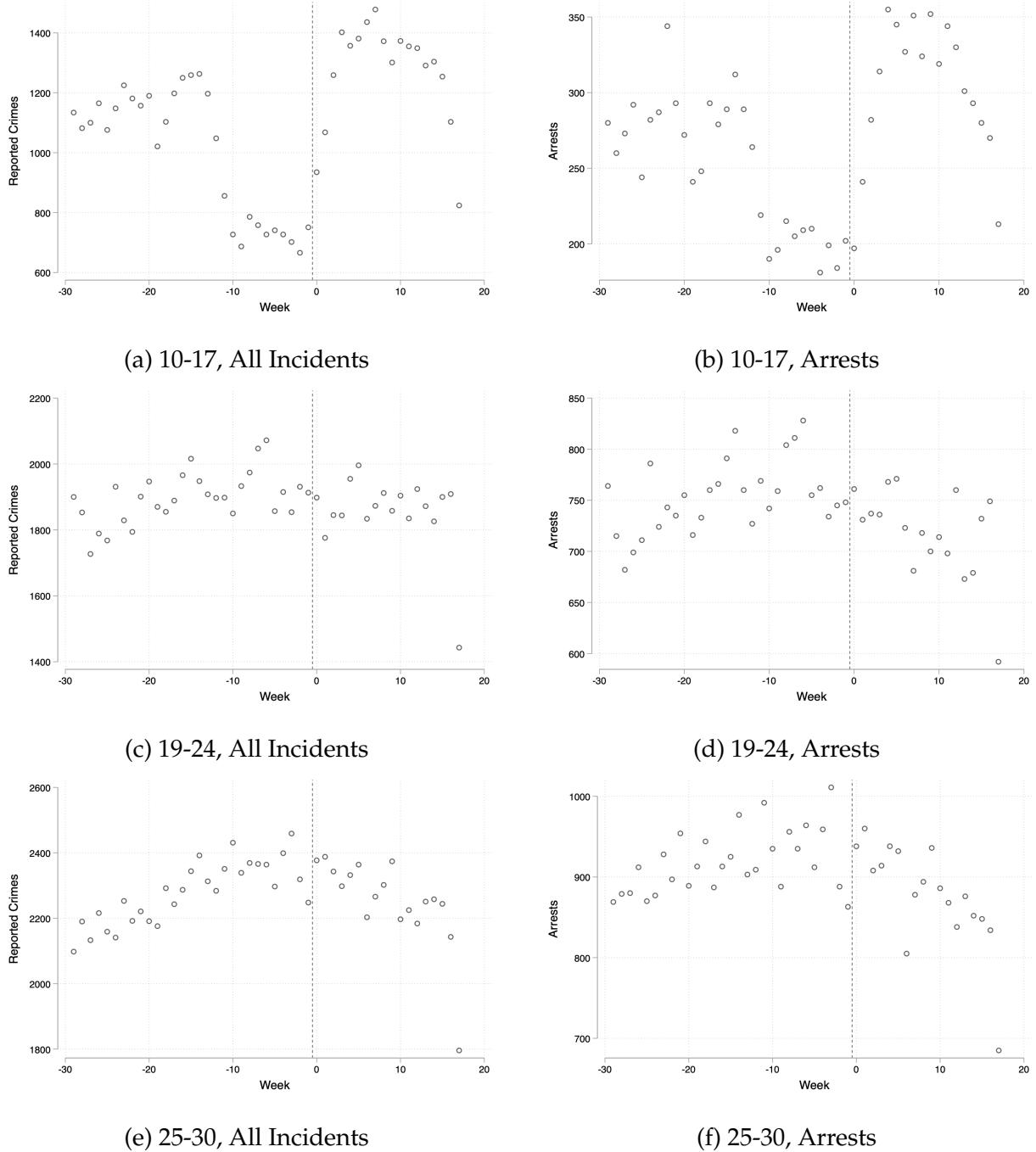
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Figure 1: Reported Crimes and Arrests by Week



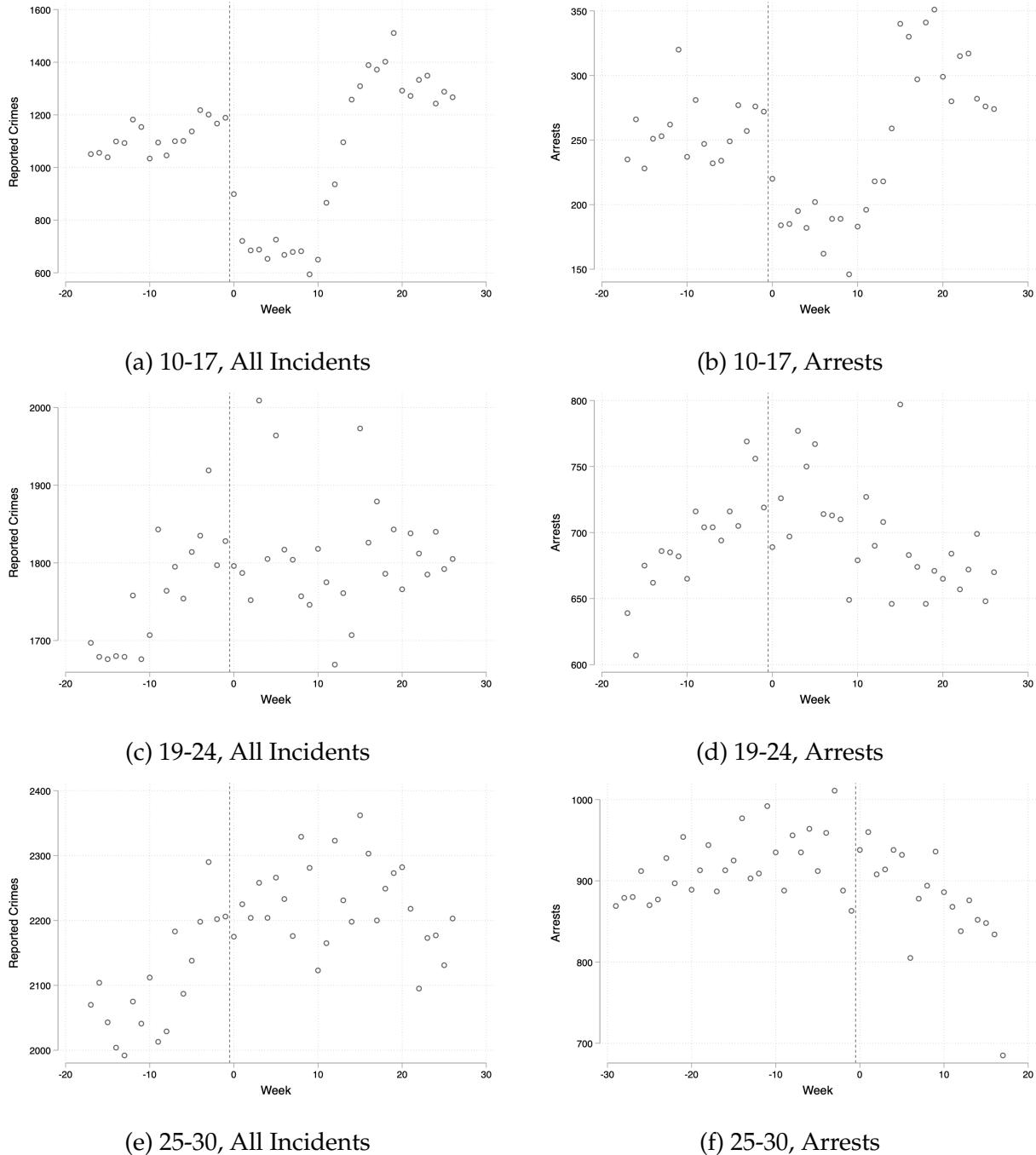
Notes: These figures show the total number of reported crimes by week. Panels A, C, and E show the total number of reported crimes, and Panels B, D, and F show the total number of arrests and times taken into custody (a subset of the total number of incidents). Panels A and B are limited to the offender being 10-17 years old; Panels C and D (E and F) are limited to the offender being 19-24 (25-30) years old. Data source: 2017-2019 NIBRS. Week 1 starts on the first Monday of the year. Weeks 0, 52, and 53 are excluded.

Figure 2: Reported Crimes and Arrests by Week Relative to School Start Date



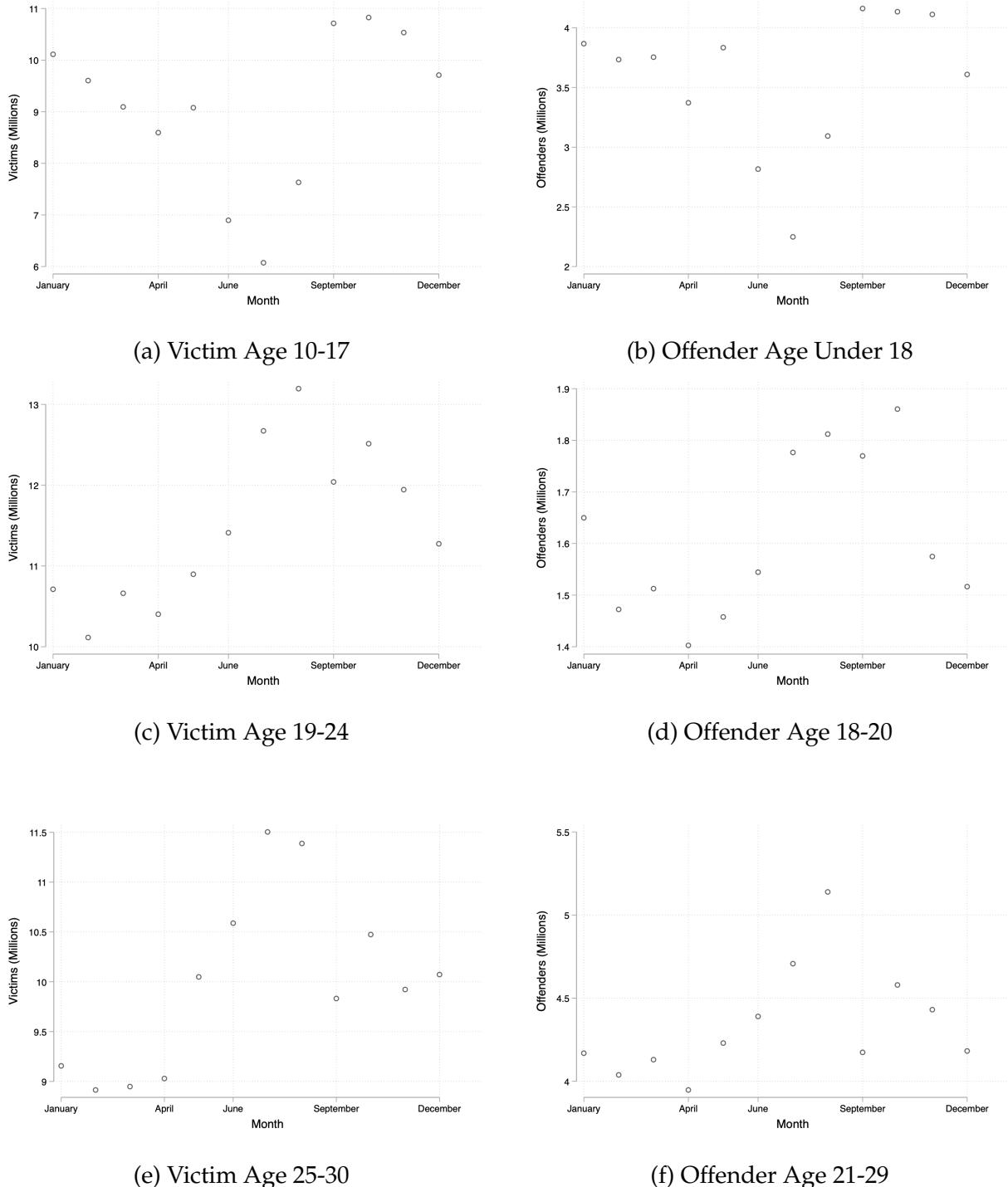
Notes: These figures show a regression discontinuity for the number of crimes by week relative to school district start date. Panels A, C, and E show the total number of reported crimes, and Panels B, D, and F show the total number of arrests and times taken into custody (a subset of the total number of incidents). Panels A and B are limited to the offender being 10-17 years old; Panels C and D (E and F) are limited to the offender being 19-24 (25-30) years old. Data source: 2019 NIBRS. Week 0 is the school district starting date. Only weeks with a balanced panel are shown. A line is drawn at time -0.5.

Figure 3: Reported Crimes and Arrests by Week Relative to School End Date



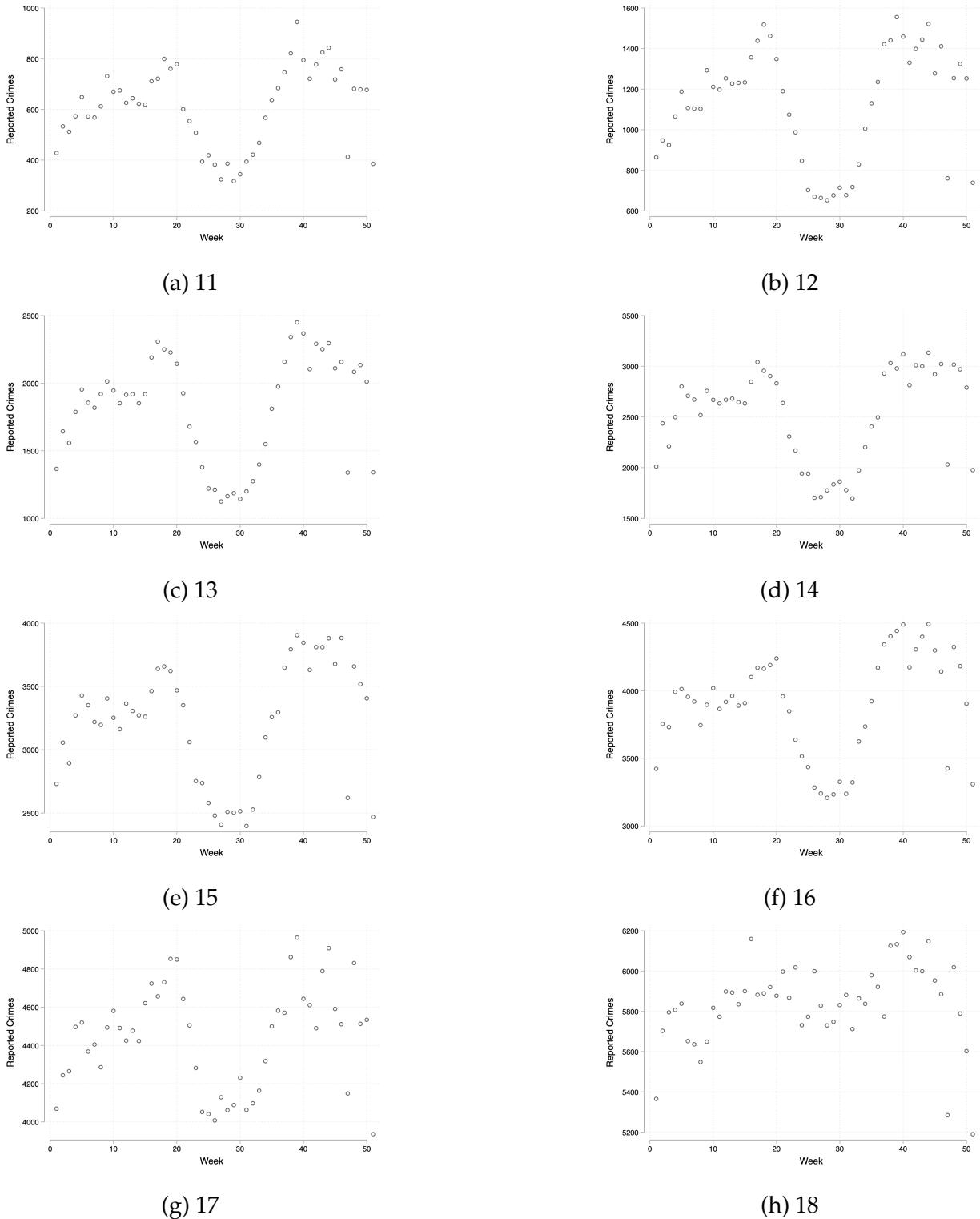
Notes: These figures show a regression discontinuity for the number of crimes by week relative to (estimated based on following year of school calendar) school district end date. Panels A, C, and E show the total number of reported crimes, and Panels B, D, and F show the total number of arrests and times taken into custody (a subset of the total number of incidents). Panels A and B are limited to the offender being 10-17 years old; Panels C and D (E and F) are limited to the offender being 19-24 (25-30) years old. Data source: 2019 NIBRS. Week 0 is the school district starting date. Only weeks with a balanced panel are shown. A line is drawn at time -0.5.

Figure 4: Crimes by Month, National Crime Victimization Survey Data, by Victim/Offender



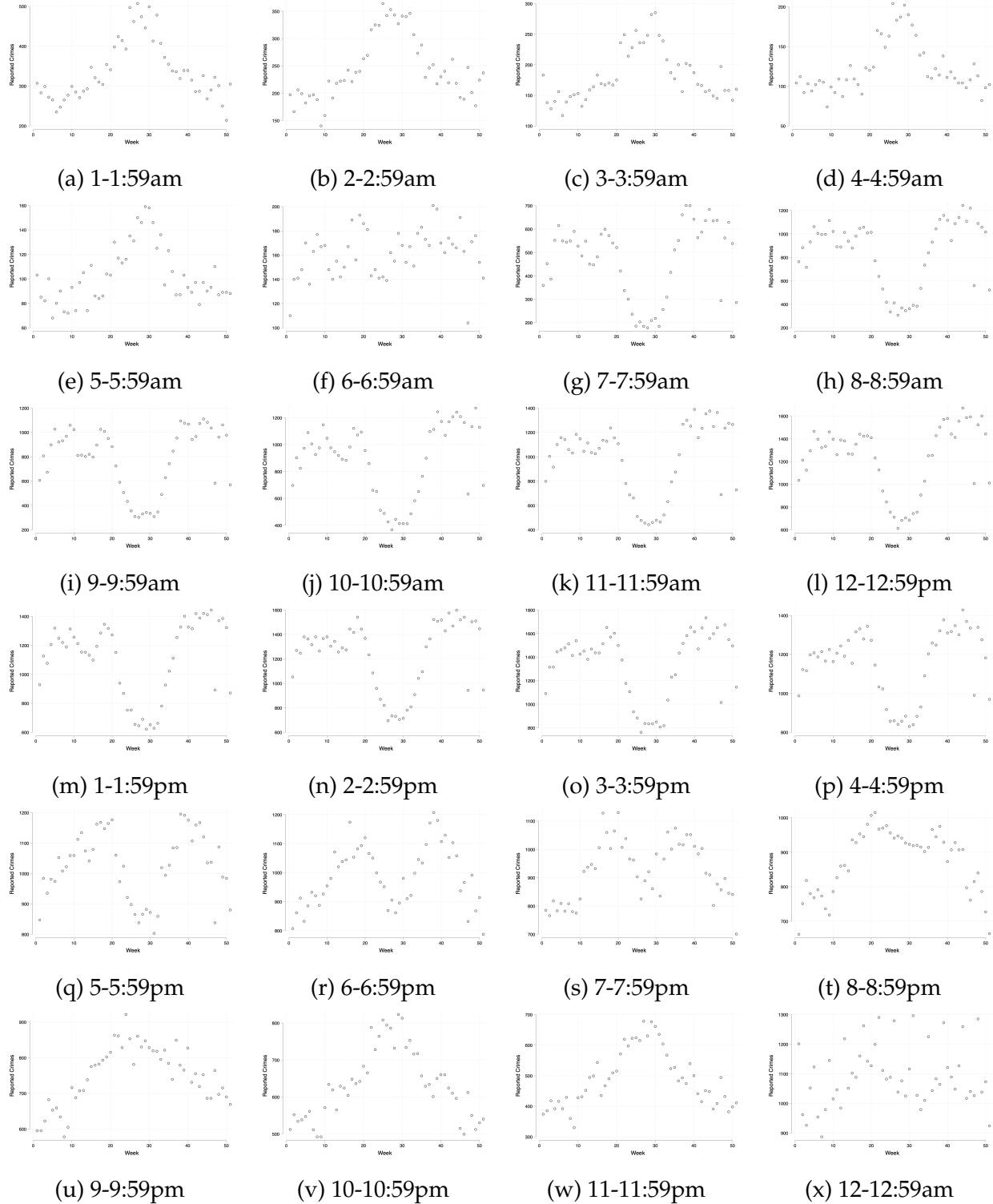
Notes: These figures show the number of crimes by month using data from the National Crime Victimization Survey from 1992 to 2020. Panels A, C, and E are for victims, and Panels B, D, and F are for offenders. Panel A is limited to the victim being 10-17 years old; Panel C (E) is limited to the victim being 19-24 (25-30) years old. Panel B is limited to the offender being 17 and younger; Panels D (F) is limited to the offender being 18-20 (21-29) years old. The offender age bin is often unobserved, leading to few observations for offenders than for victims.

Figure 5: Reported Crimes by Week, by Age of Offender



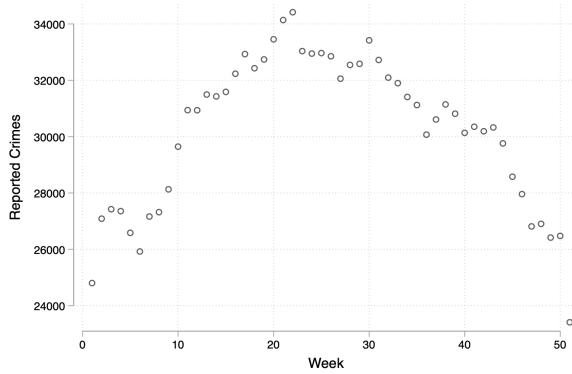
Notes: These figures show the total number of reported crimes by week. Each panel corresponds to a different age of offender (from age 11 to age 18). The data source is 2017-2019 NIBRS. Week 1 starts on the first Monday of the year. Weeks 0, 52, and 53 are excluded.

Figure 6: Crimes by Week, Age 10-17, by Hour of the Day

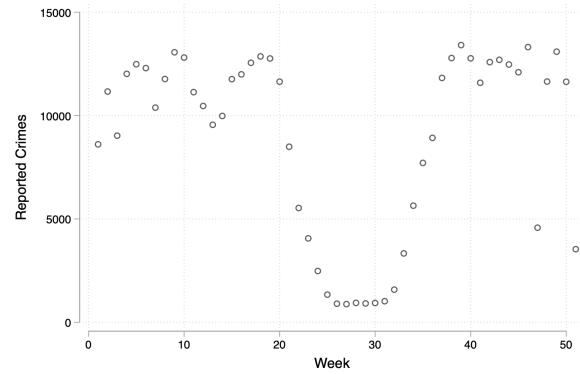


Notes: These figures show the total number of reported crimes by week for ages 10-17. Each panel corresponds to a different hour of the day. The data source is 2017-2019 NIBRS. Week 1 starts on the first Monday of the year. Weeks 0, 52, and 53 are excluded.

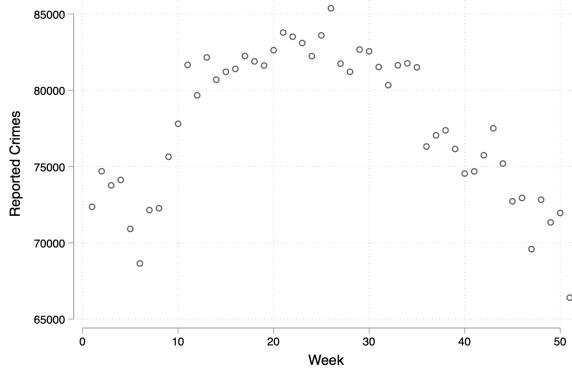
Figure 7: Reported Crimes by Week, Age 10-17, by Location



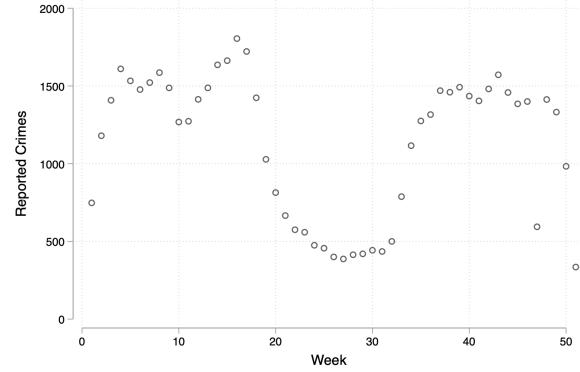
(a) Not in School; 10-17



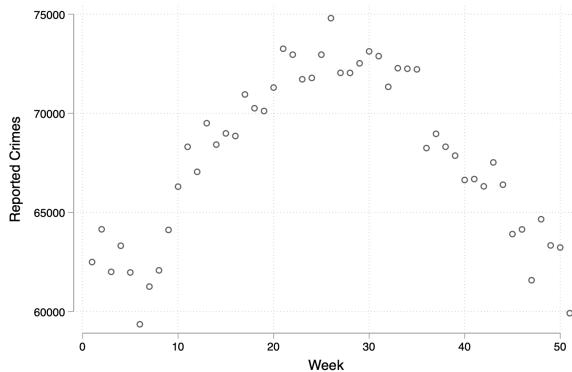
(b) In School; 10-17



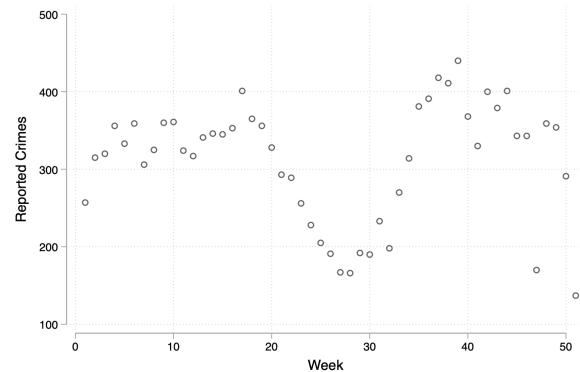
(c) Not in School; 19-24



(d) In School; 19-24



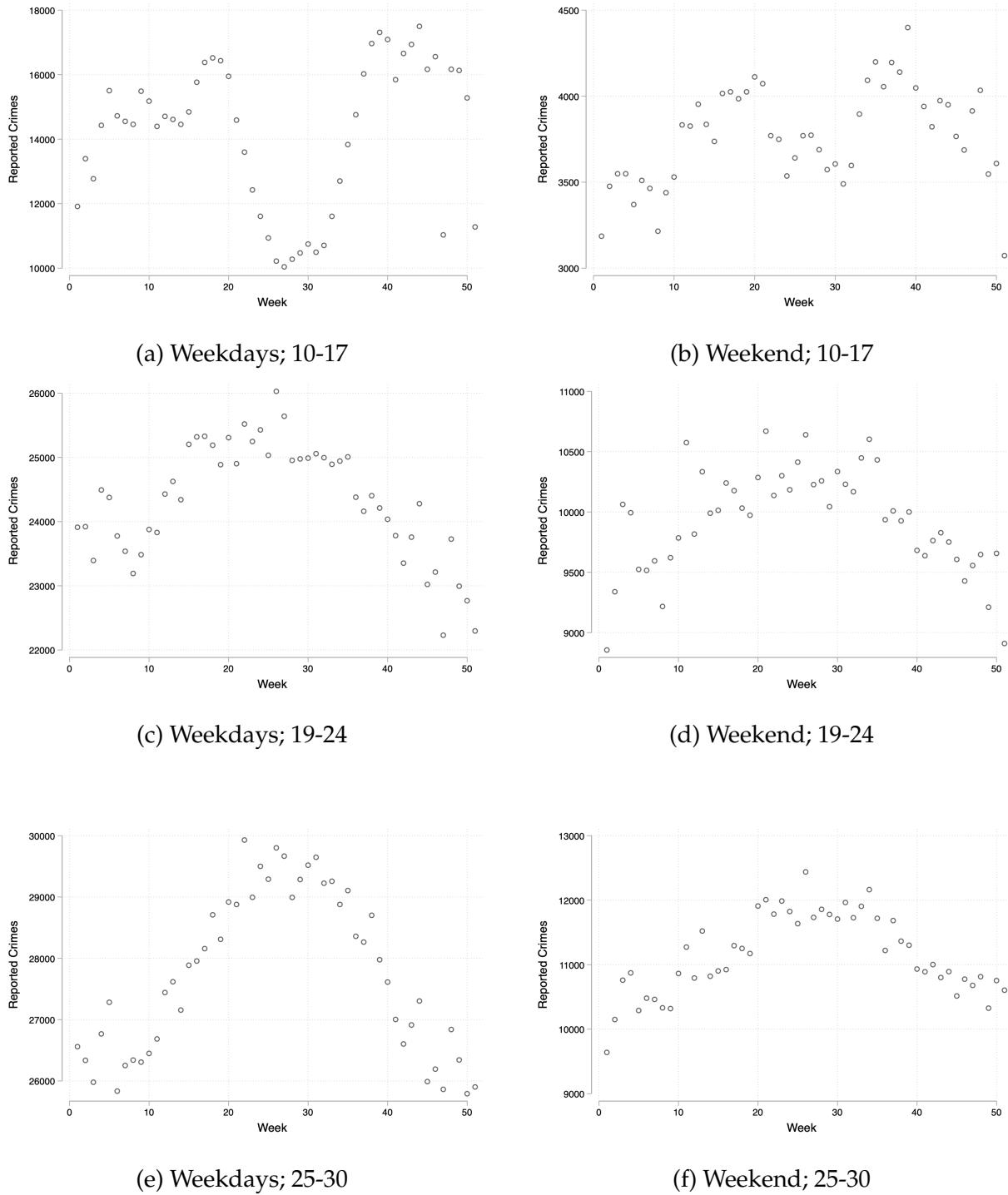
(e) Not in School; 25-30



(f) In School; 25-30

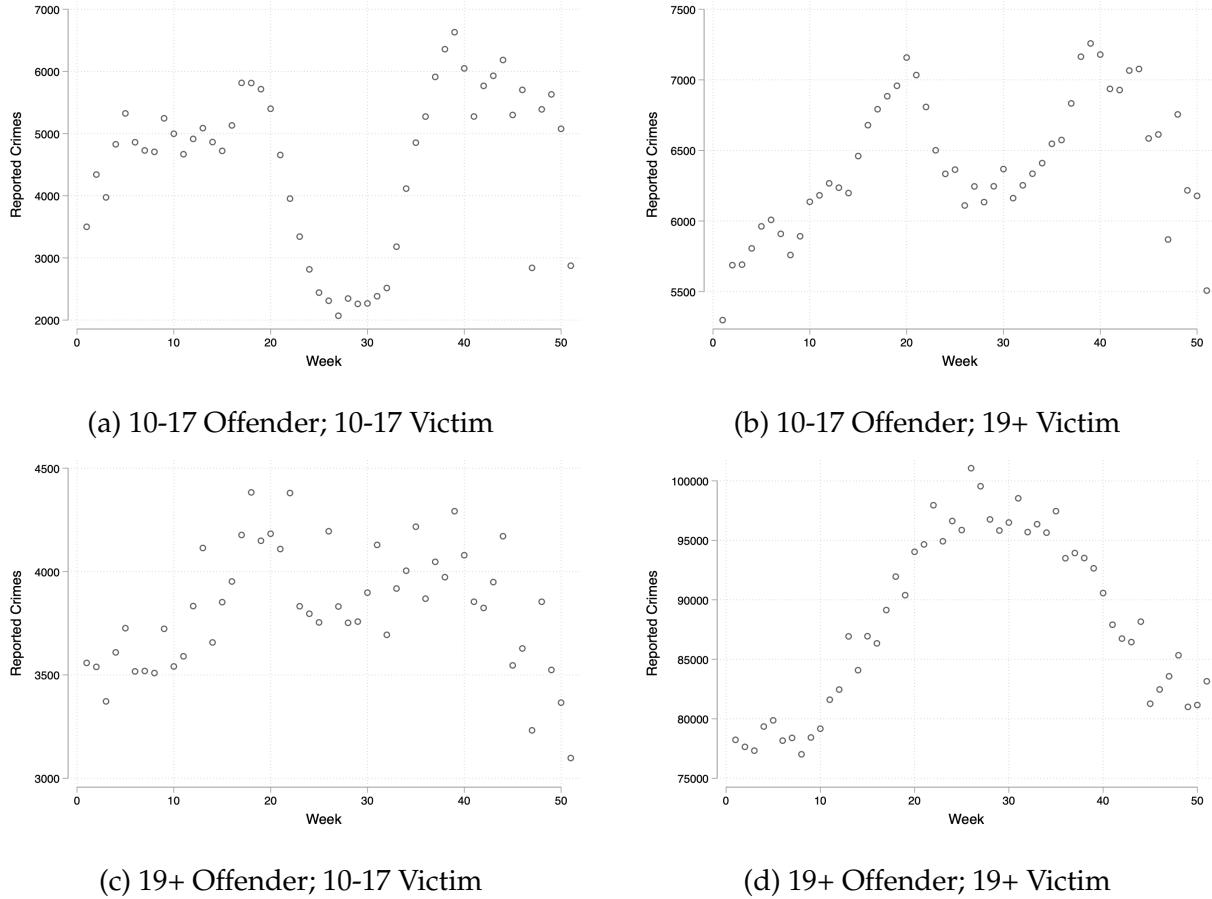
Notes: These figures show the total number of reported crimes by week for crimes not occurring in schools/colleges (Panels A, C, and E) and for crimes occurring in schools/colleges (Panels B, D, and F). Panels A and B are limited to the offender being 10-17 years old; Panels C and D (E and F) are limited to the offender being 19-24 (25-30) years old. The data source is 2010-2016 NIBRS, explaining the larger sample size. Week 1 starts on the first Monday of the year. Weeks 0, 52, and 53 are excluded.

Figure 8: Reported Crimes by Week, by Weekdays vs. Weekend



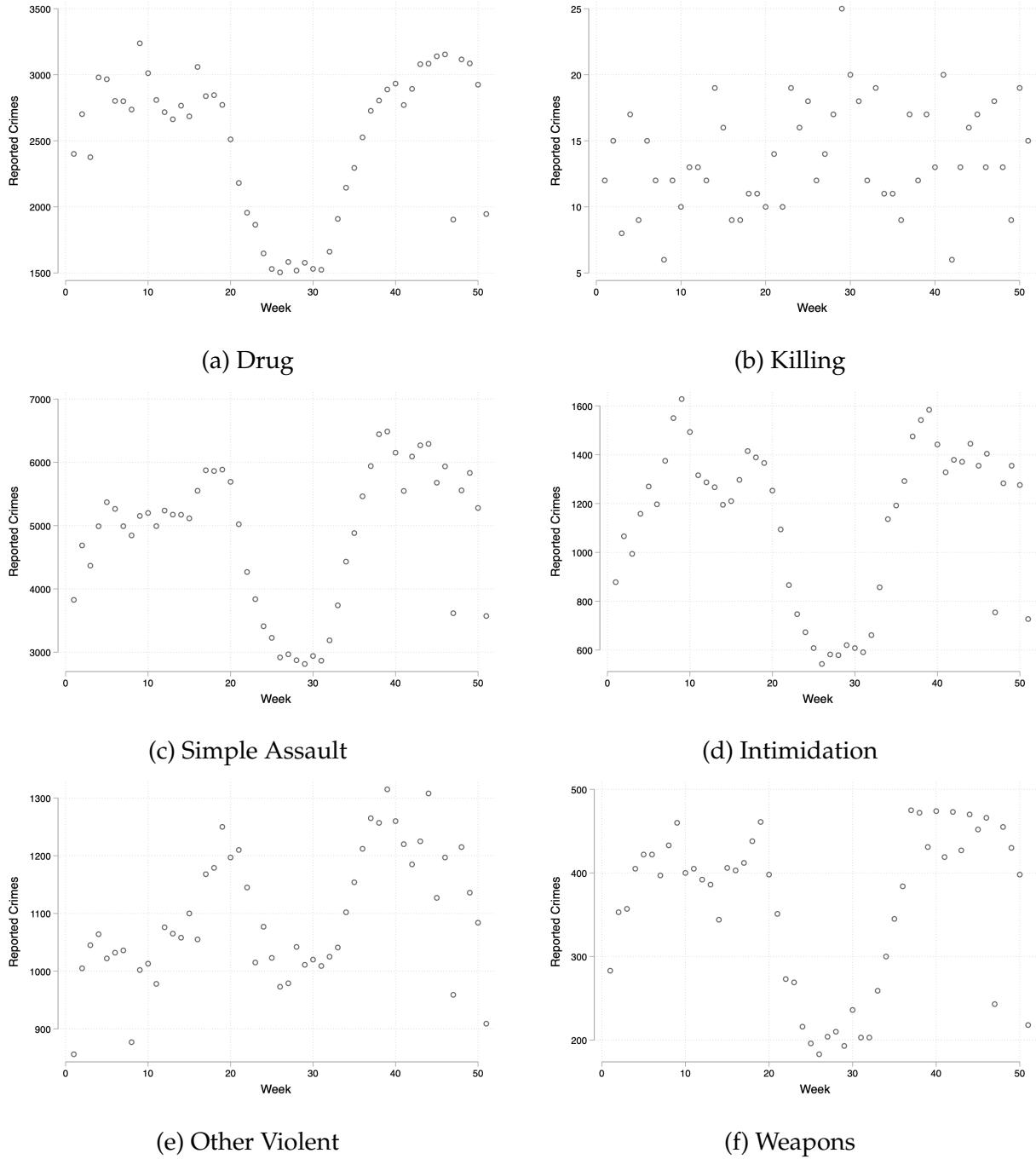
Notes: These figures show the total number of reported crimes by week for crimes not occurring on weekdays (Monday through Friday; Panels A, C, and E) and for crimes occurring on weekends (Saturday and Sunday; Panels B, D, and F). Panels A and B are limited to the offender being 10-17 years old; Panels C and D (E and F) are limited to the offender being 19-24 (25-30) years old. The data source is 2017-2019 NIBRS. Week 1 starts on the first Monday of the year. Weeks 0, 52, and 53 are excluded.

Figure 9: Reported Crimes by Week, by Offender and Victim Age Categories



Notes: These figures show the total number of reported crimes by week for crimes when the sample limited to 10-17 year old offender and 10-17 year old victim (Panel A); 10-17 year old offender and 19+ year old victim (Panel B); 19+ year old offender and 10-17 year old victim (Panel C); and 19+ year old offender and 19+ year old victim (Panel D). The data source is 2017-2019 NIBRS. Week 1 starts on the first Monday of the year. Weeks 0, 52, and 53 are excluded.

Figure 10: Reported Crimes by Week, Age 10-17, by Type of Offense



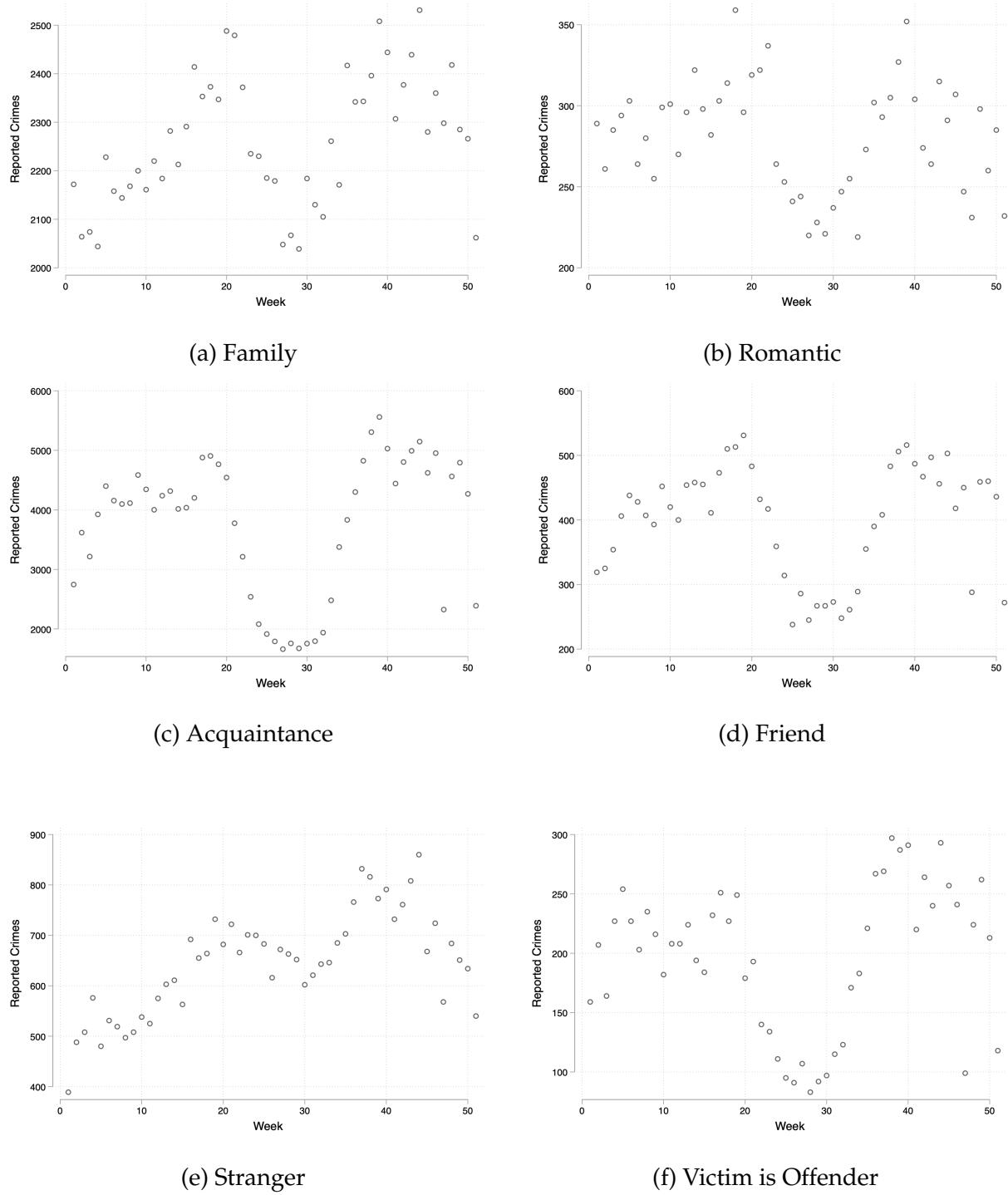
Notes: These figures show the total number of reported crimes by week for offenders aged 10-17. Each panel corresponds to a different type of crime. Panel a) shows drug crimes; Panel b) shows killings; Panel c) shows simple assault; Panel d) shows intimidation; Panel e) shows other violent crime; and Panel f) shows weapons. Categories are as follows: Drug: drug equipment violations; drug/narcotic violations. Killing: justifiable homicide; murder/nonnegligent manslaughter; negligent manslaughter. Simple Assault: simple assault. Intimidation: intimidation. Other Violent: aggravated assault; kidnapping/abduction; robbery. Weapons: weapon law violations. The data source is 2017-2019 NIBRS. Week 1 starts on the first Monday of the year. Weeks 0, 52, and 53 are excluded.

Figure 11: Reported Crimes by Week, Age 10-17, by Type of Offense (Continued)



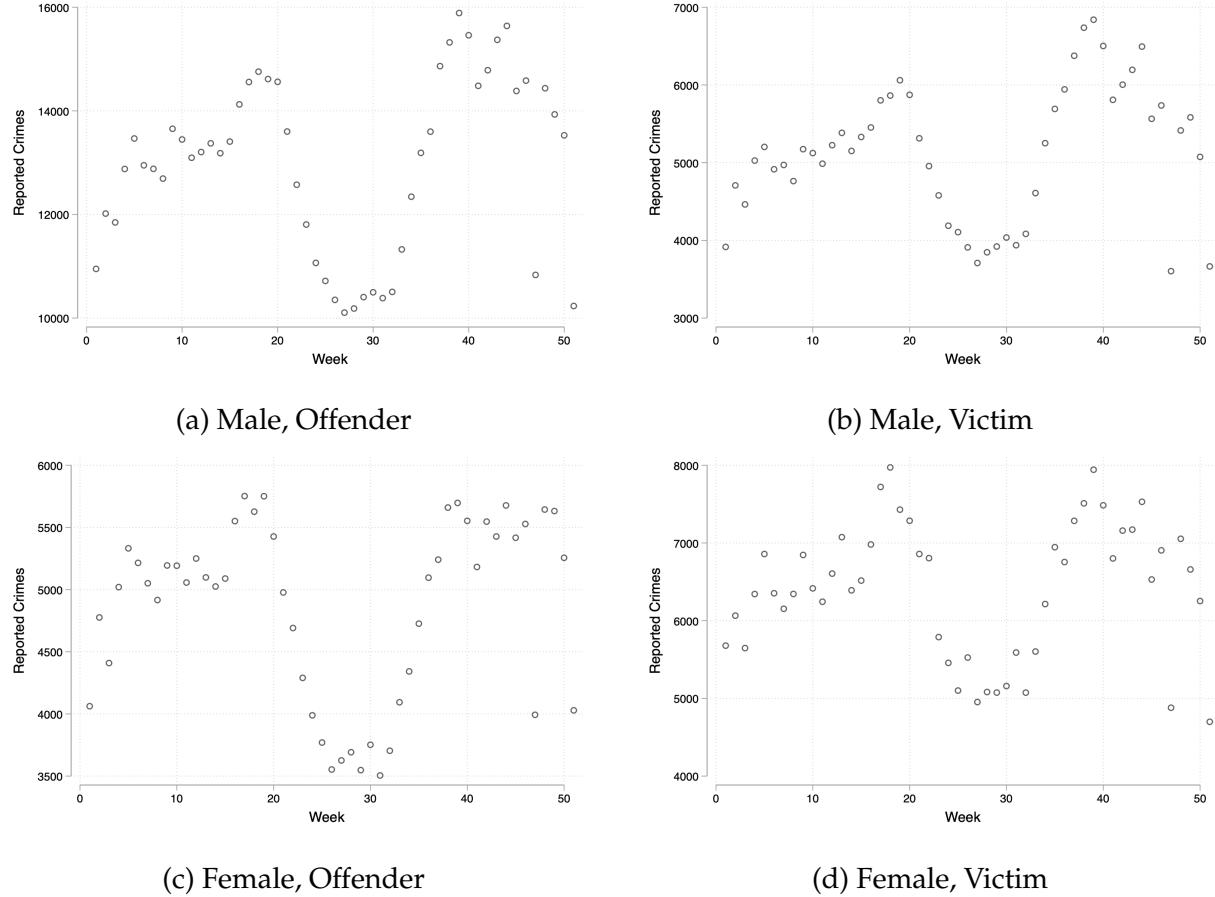
Notes: These figures show the total number of reported crimes by week for offenders aged 10-17. Each panel corresponds to a different type of crime. Panel a) shows theft; Panel b) shows property damage/vandalism; Panel c) shows sexual assault; and Panel d) shows other non-violent. Categories are as follows: Theft: all other larceny; burglary/breaking and entering; motor vehicle theft; pocket-picking; purse-snatching; shoplifting; theft from building; theft from coin-operated machine or device; theft from motor vehicle; theft of motor vehicle parts/accessories. Property Damage/Vandalism: destruction/damage/vandalism of property. Sexual Assault: fondling (incident liberties/child molest); incest; rape; sexual assault with an object; sodomy; statutory rape. Other Non-violent: animal cruelty; arson; assisting or promoting prostitution; betting/wagering; bribery; counterfeiting/forgery; credit card/ATM fraud; embezzlement; extortion/blackmail; false pretenses/swindle/confidence game; gambling equipment violations; hacking/computer invasion; human trafficking - commercial sex acts; human trafficking - involuntary servitude; identity theft; impersonation; operating/promoting/assisting gambling; pornography/obscene material; prostitution; purchasing prostitution; sports tampering; stolen property offenses (receiving, selling, etc.); welfare fraud; wire fraud. Unknown crime types are omitted. The data source is 2017-2019 NIBRS. Week 1 starts on the first Monday of the year. Weeks 0, 52, and 53 are excluded.

Figure 12: Reported Crimes by Week, Age 10-17, by Relationship of Offender to Victim



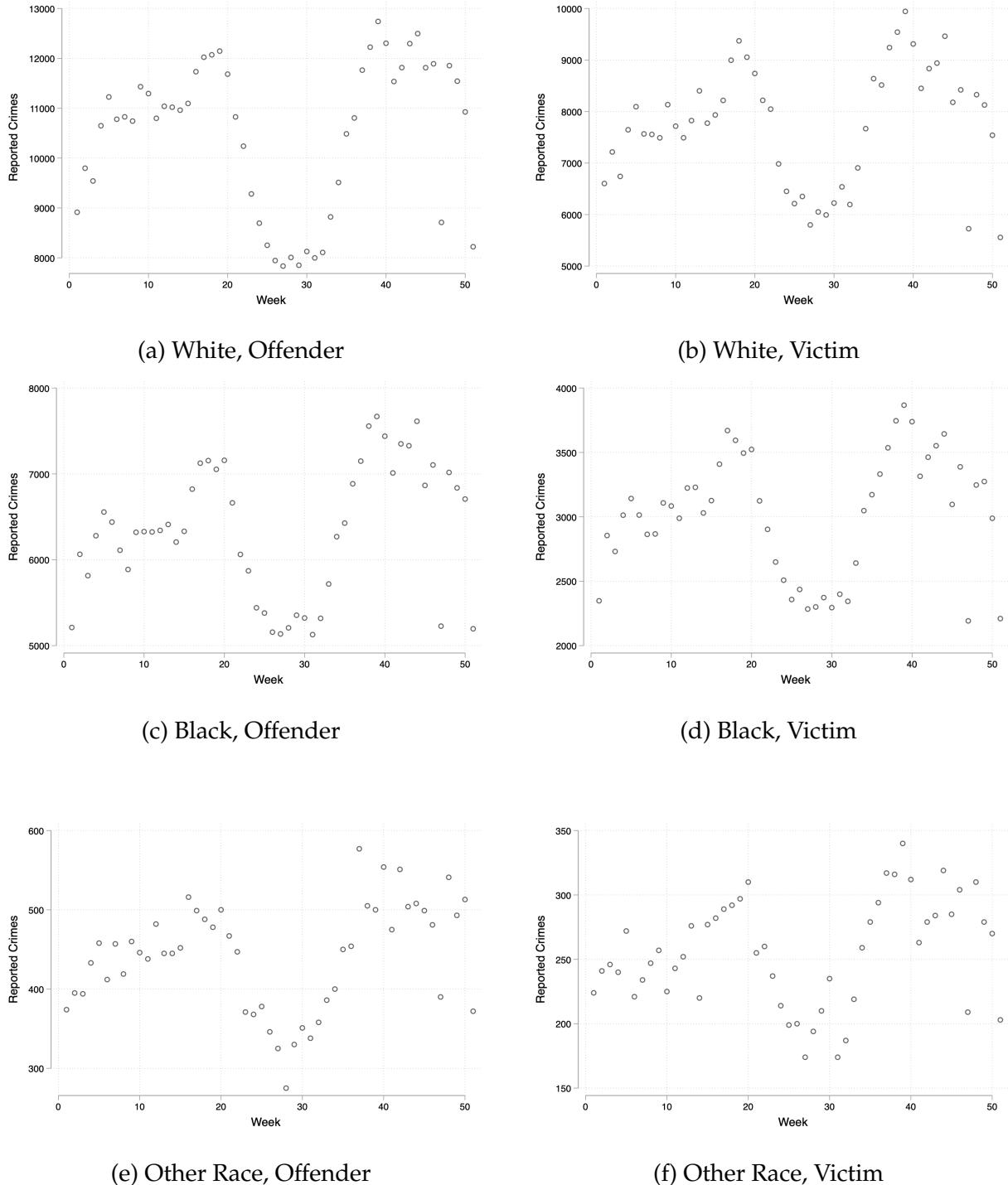
Notes: These figures show the total number of reported crimes by week for ages 10-17. Each panel corresponds to the relationship of the first offender to the first victim. Family includes spouse, common-law spouse, parent, sibling, child, grandparent, grandchild, in-law, stepparent, stepchild, stepsibling, and other family member. Romantic includes boyfriend/girlfriend, and homosexual relationship. Acquaintance includes acquaintance, neighbor, babysitter (the baby), child of boyfriend/girlfriend, employee, employer, otherwise known, ex-spouse, and ex-relationship (boyfriend/girlfriend). Friend includes friend. Stranger includes stranger. Victim Is Offender includes victim was offender. The data source is 2017-2019 NIBRS. Week 1 starts on the first Monday of the year. Weeks 0, 52, and 53 are excluded.

Figure 13: Reported Crimes by Week, Age 10-17, by Male/Female and Offender/Victim



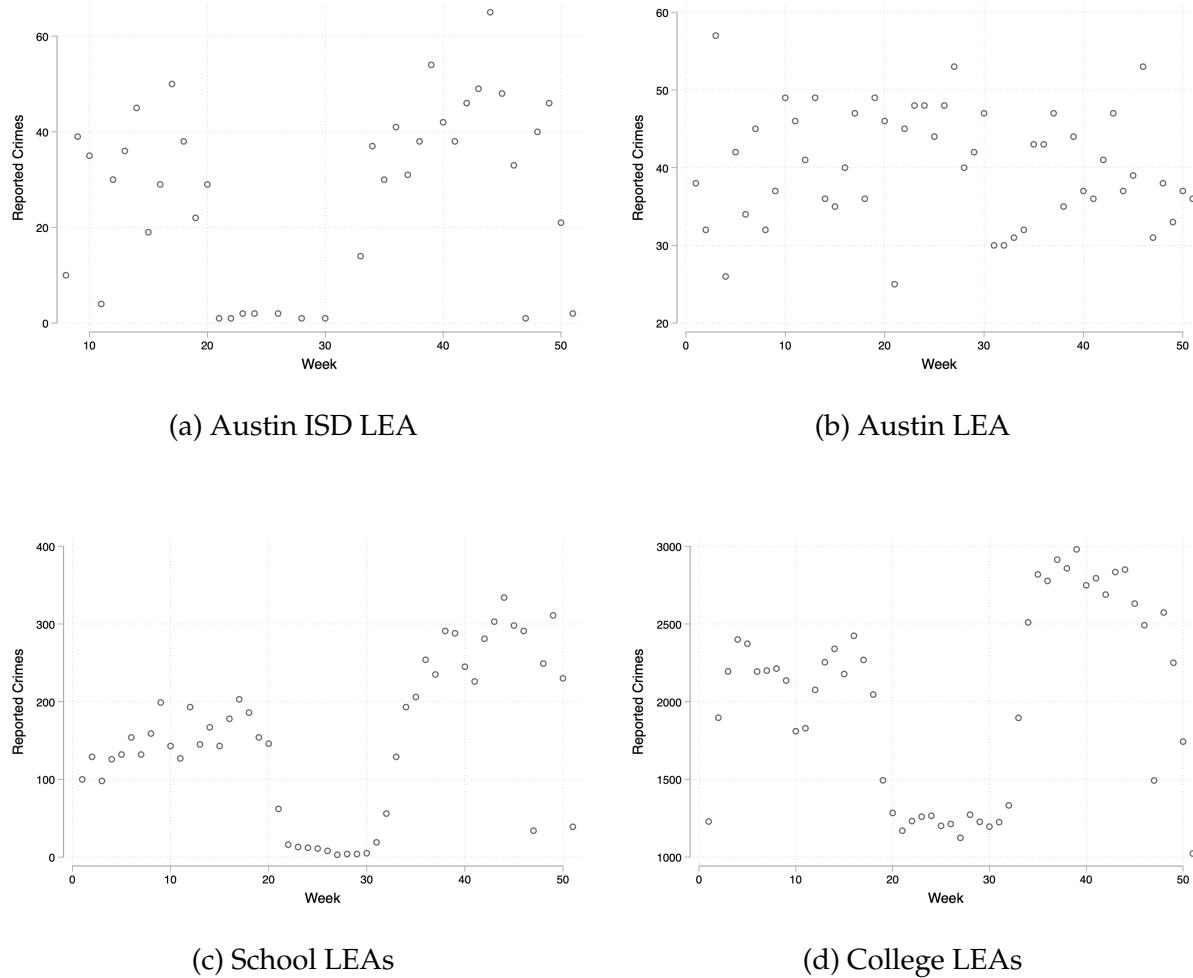
Notes: These figures show the total number of reported crimes by week for ages 10-17. Each panel corresponds to a male/female+offender/victim pair. The data source is 2017-2019 NIBRS. Week 1 starts on the first Monday of the year. Weeks 0, 52, and 53 are excluded.

Figure 14: Reported Crimes by Week, Age 10-17, by Black/White/Other Race and Offender/Victim



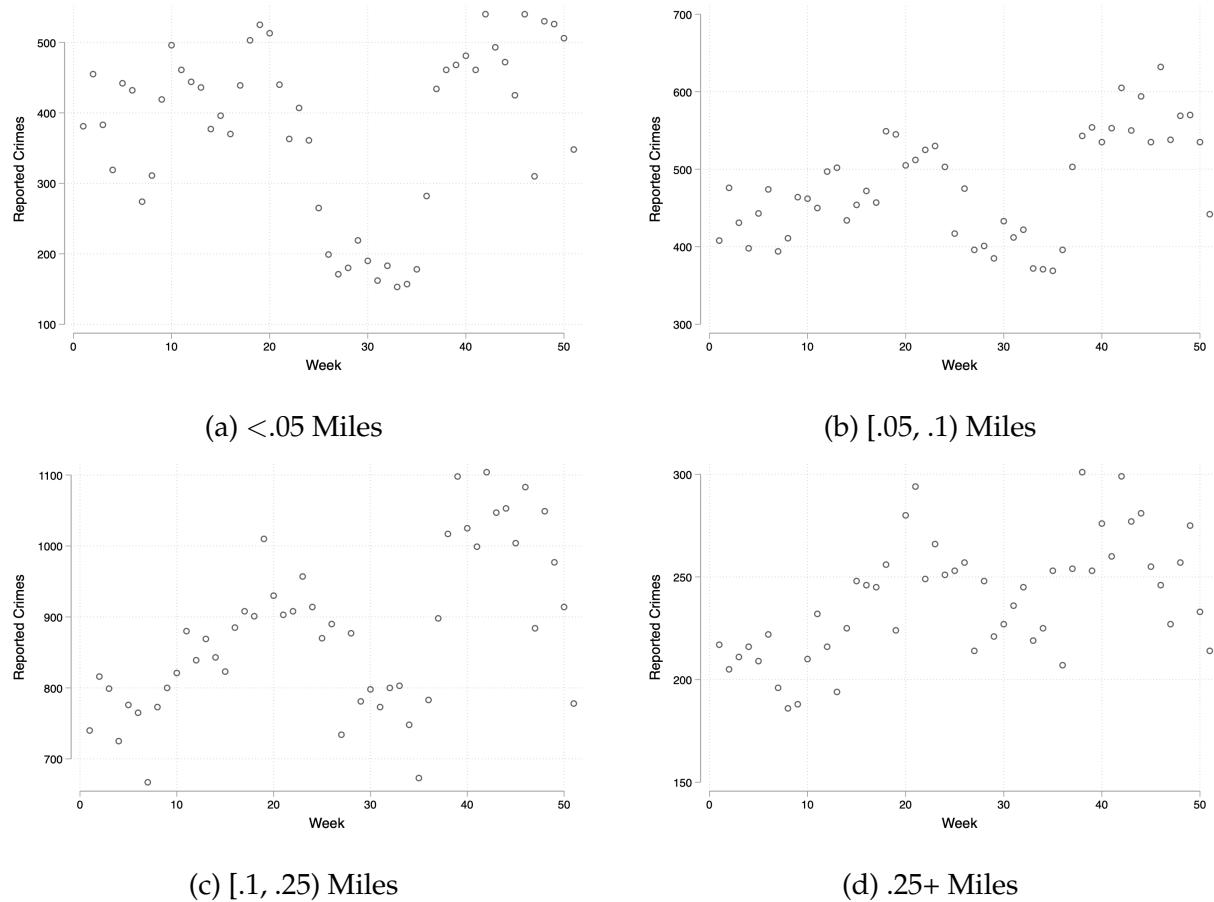
Notes: These figures show the total number of reported crimes by week for ages 10-17. Each panel corresponds to a Black/White/Other Race+offender/victim pair. Other Race includes American Indian, Alaskan Native, Asian, and Pacific Islander, and Native Hawaiian. The data source is 2017-2019 NIBRS. Week 1 starts on the first Monday of the year. Weeks 0, 52, and 53 are excluded.

Figure 15: Reported Crimes by Week, School-based LEAs



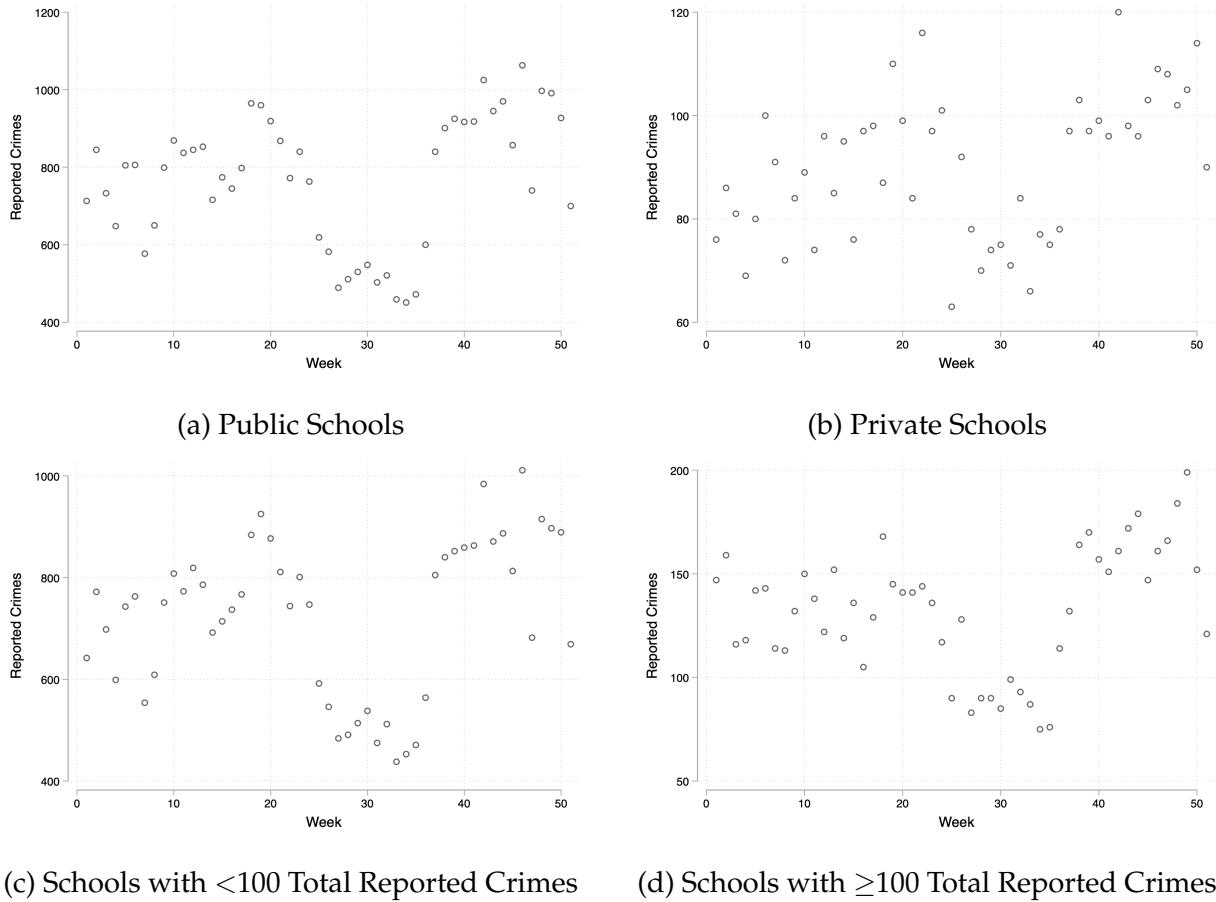
Notes: These figures show the total number of reported crimes by week for ages 10-17. Panel A is for the Austin Independent School District law enforcement agency (LEA). Panel B is for the Austin LEA. Panel C is for school LEAs, identified by their name including "school(s)", "ISD", or "I.S.D.". Panel D is for college LEAs, identified by their name including "college" or "university." Age is 10-17 for all panels except Panel D, which is unrestricted. The data source is 2017-2019 NIBRS. Week 1 starts on the first Monday of the year. Weeks 0, 52, and 53 are excluded.

Figure 16: Reported Crimes by Week, Age 17 and Younger, New York City, Donut Hole by Distance to Nearest School



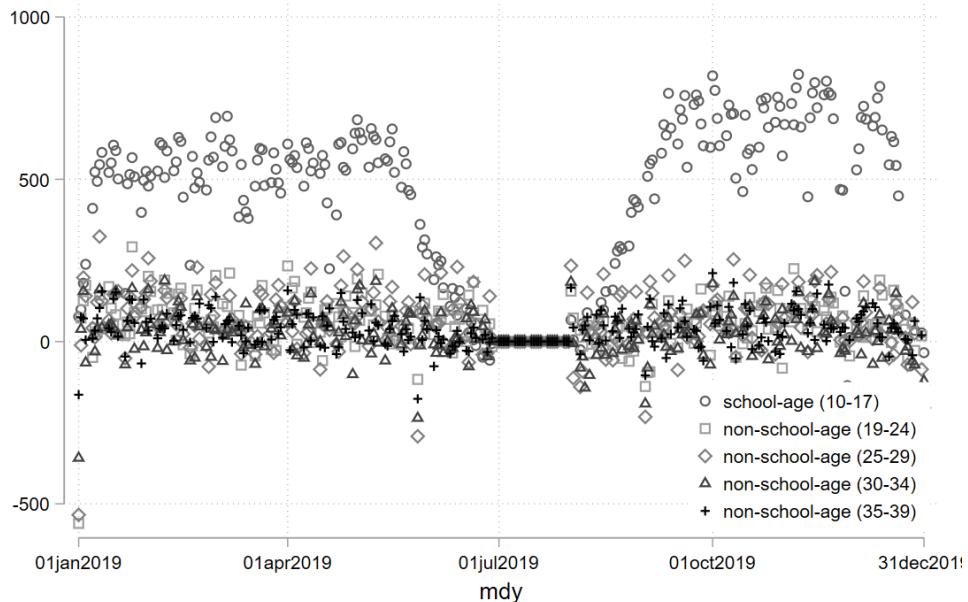
Notes: These figures show the total number of reported crimes by week for ages 17 and younger using New York City data. Each observation is matched, using latitudes and longitudes, to the nearest school geocode using data from NCES. Each panel presents a graph limiting to reported crimes occurring in a certain distance range from the nearest school: less than 0.05 miles for Panel A; between 0.05 and 0.1 miles for Panel B; between 0.1 and 0.25 miles for Panel C; and 0.25 miles and greater for Panel D. Observations are limited to those occurring between 2006-2019 (from the start of the complaint variable). Week 1 starts on the first Monday of the year. Weeks 0, 52, and 53 are excluded.

Figure 17: Reported Crimes by Week, Age 17 and Under, New York City,  $< .1$  Mile to Nearest School, by Public and Private, and by Schools with Few vs. Many Reported Crimes

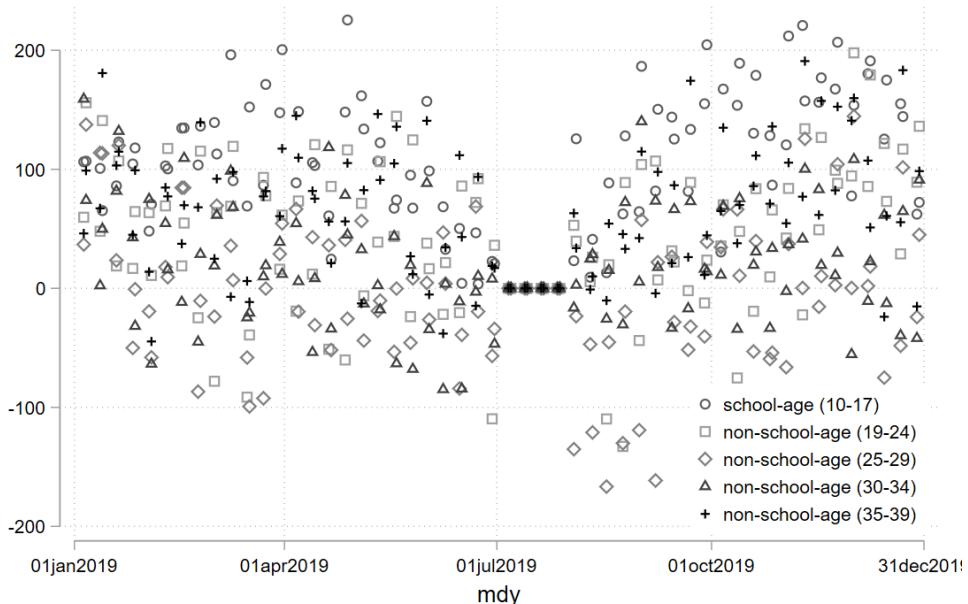


Notes: These figures show the total number of reported crimes by week for ages 17 and younger using New York City data. Each observation is matched, using latitudes and longitudes, to the nearest school geocode using data from NCES. All Panels are limited to observations occurring within 0.1 miles of the nearest school. Panel A is for public schools; Panel B is for private schools; Panel C is for schools with fewer than 100 observations over the entire sample; and Panel D is for schools with at least 100 observations over the entire sample. Observations are limited to those occurring between 2006-2019 (from the start of the complaint variable). Week 1 starts on the first Monday of the year. Weeks 0, 52, and 53 are excluded.

Figure 18: Seasonally-adjusted Reported Crime



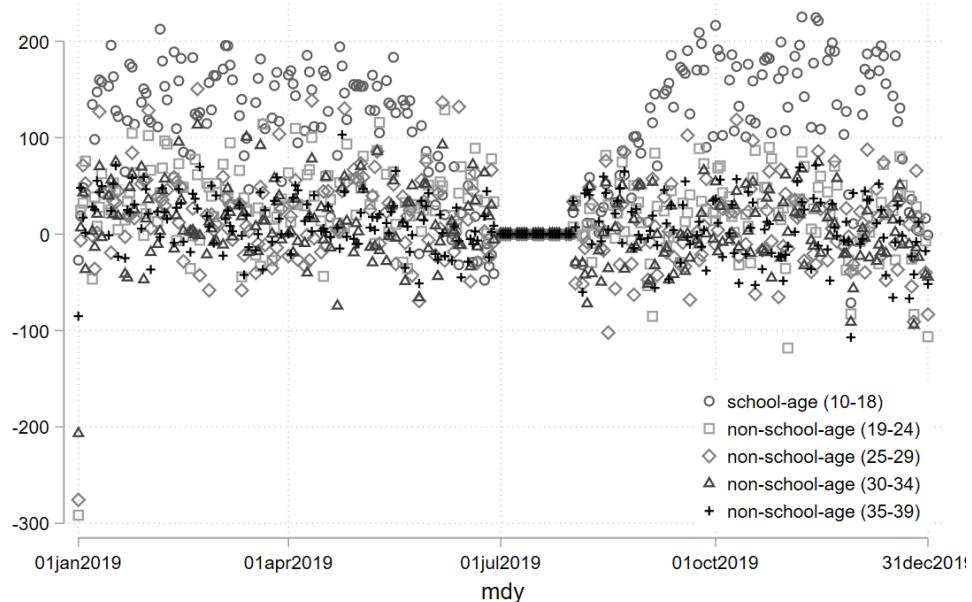
(a) Weekday Reported Crimes (residualized)



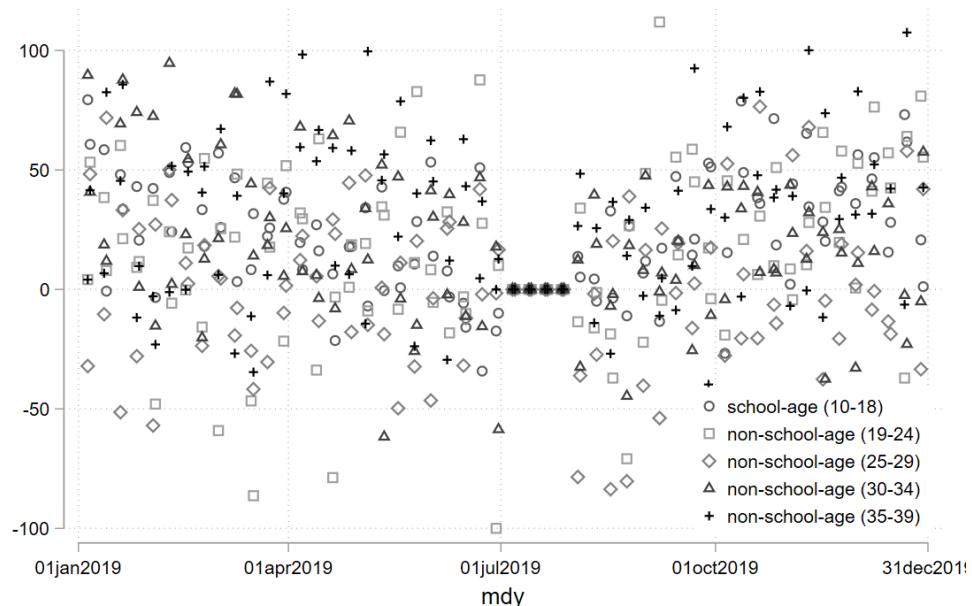
(b) Weekend Reported Crimes (residualized)

Notes: Seasonal adjustment calculated by regressing daily counts of reported crime in the 2019 NIBRS panel (by calendar day by- hour of the day -by- age of offender) on calendar day -by- age fixed effects and day-of-the-week -by- hour-of-the-day -by- age fixed effects for crime reported outside of the school calendar and school hours (in July or between 8pm and 6am). Subtracting these fixed effects from reported cell-level crime and summing the resulting residual by calendar day produces the (daily) residuals presented above (pegged to July 1st, 2019). The top panel shows the residuals for weekdays, and the bottom panel shows residuals for weekends.

Figure 19: Seasonally-adjusted Reported Arrests



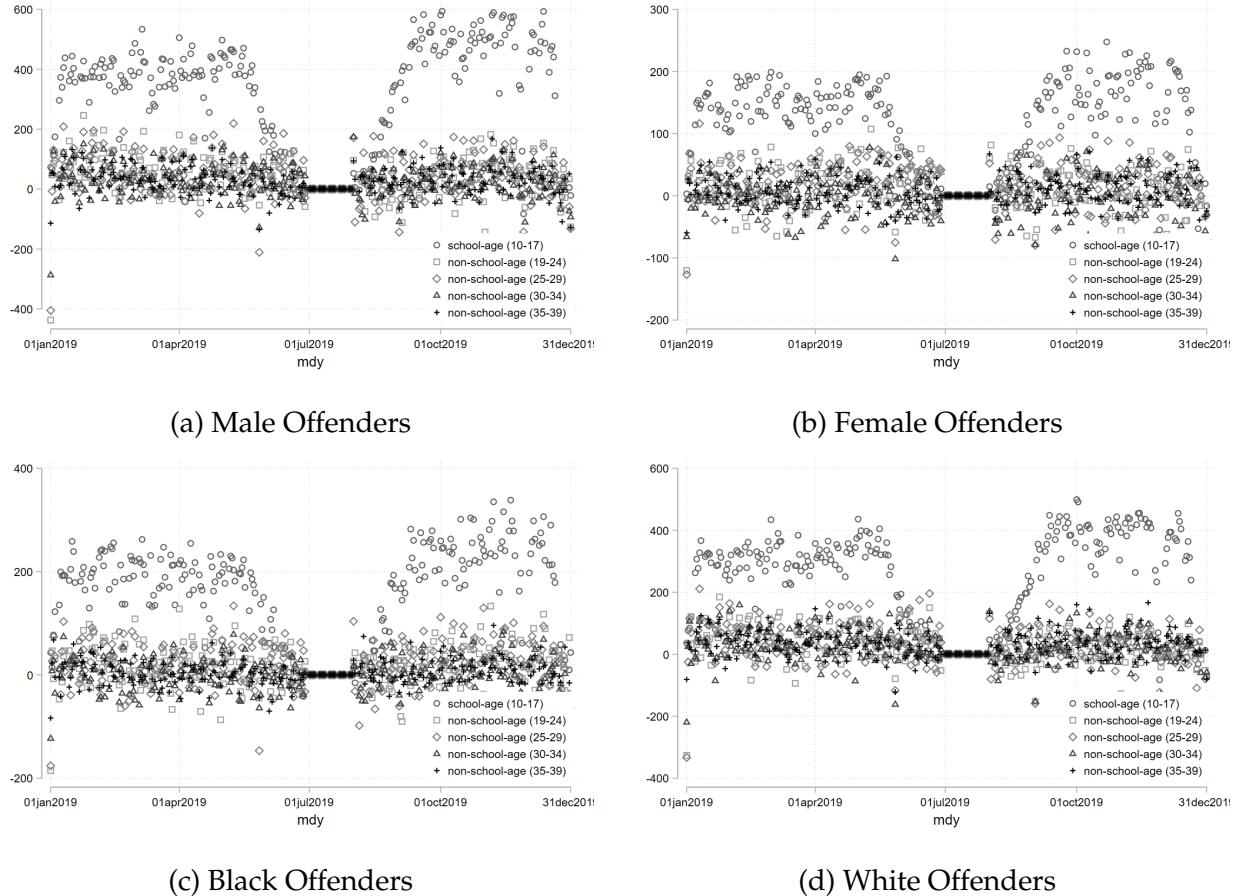
(a) Weekday Reported Arrests (residualized)



(b) Weekend Reported Arrests (residualized)

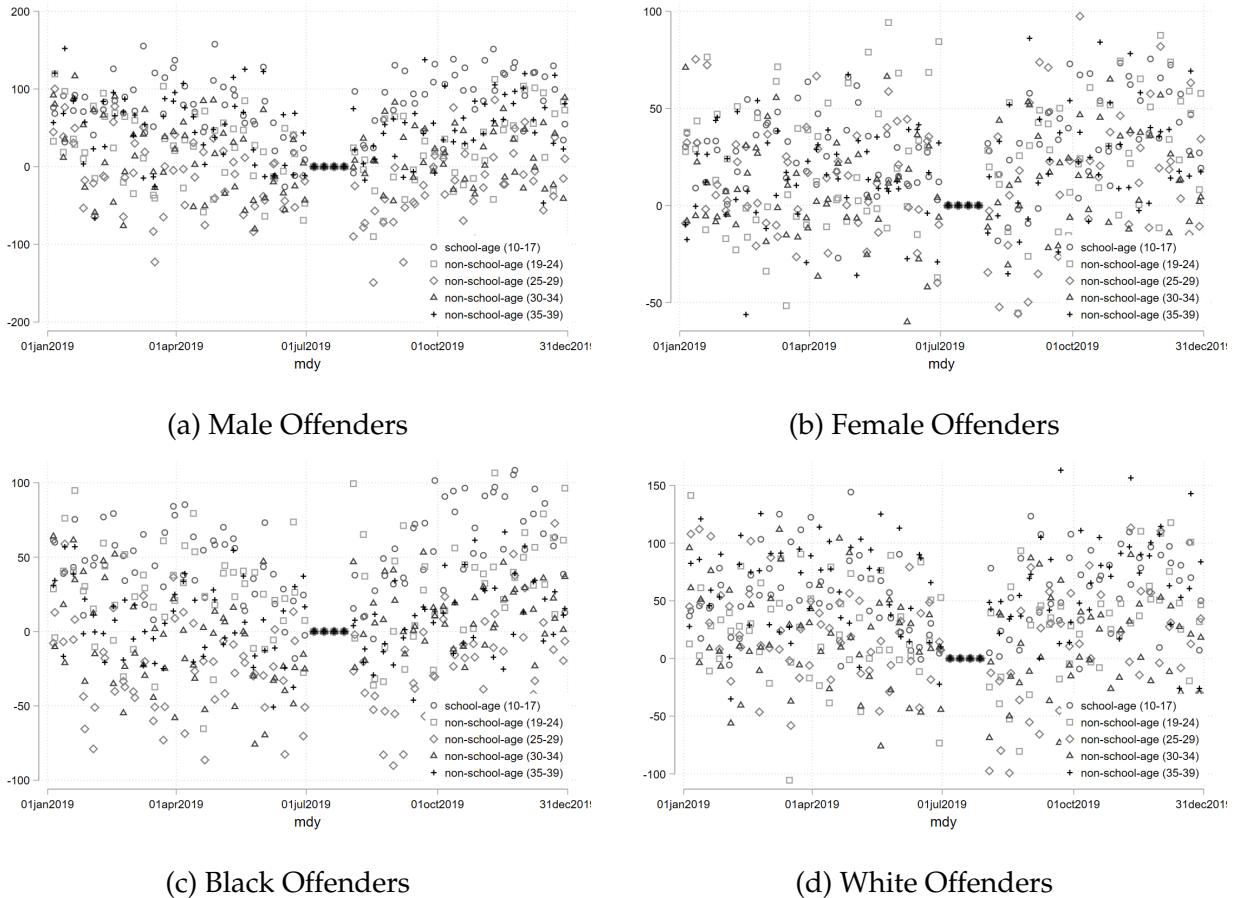
Notes: Seasonal adjustment calculated by regressing daily counts of reported arrests in the 2019 NIBRS panel (by calendar day by- hour of the day -by- age of offender) on calendar day -by- age fixed effects and day-of-the-week -by- hour-of-the-day -by- age fixed effects for arrests reported outside of the school calendar and school hours (in July or between 8pm and 6am). Subtracting these fixed effects from reported cell-level arrests and summing the resulting residual by calendar day produces the (daily) residuals presented above (pegged to July 1st, 2019). The top panel shows the residuals for weekdays, and the bottom panel shows residuals for weekends.

Figure 20: Weekday Seasonally-adjusted Reported Crime, by Sex and Race



Notes: Seasonal adjustment calculated by regressing daily counts of reported arrests in the 2019 NIBRS panel (by calendar day by- hour of the day -by- age of offender) on calendar day -by- age fixed effects and day-of-the-week -by- hour-of-the-day -by- age fixed effects for arrests reported outside of the school calendar and school hours (in July or between 8pm and 6am). Subtracting these fixed effects from reported cell-level arrests and summing the resulting residual by calendar day produces the (daily) residuals presented above (pegged to July 1st, 2019). The top left panel shows the residuals for male offenders, , and the bottom panel shows residuals for weekends.

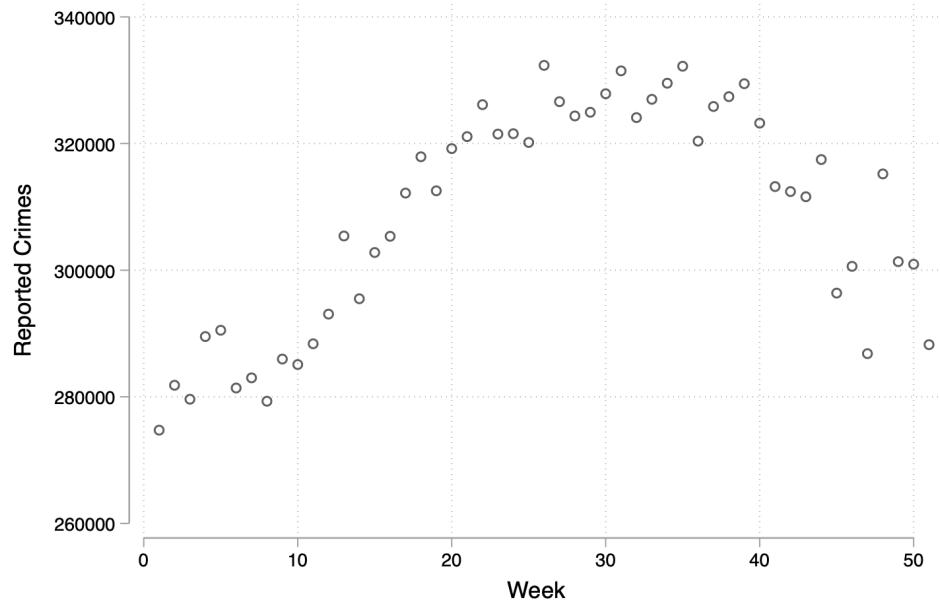
Figure 21: Weekend Seasonally-adjusted Reported Crime, by Sex and Race



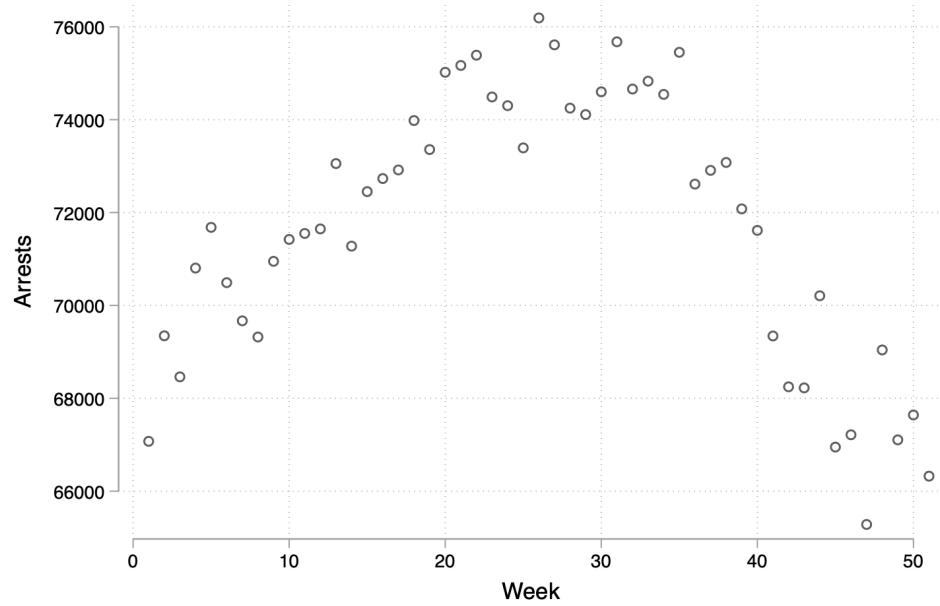
Notes: Seasonal adjustment calculated by regressing daily counts of reported arrests in the 2019 NIBRS panel (by calendar day by- hour of the day -by- age of offender) on calendar day -by- age fixed effects and day-of-the-week -by- hour-of-the-day -by- age fixed effects for arrests reported outside of the school calendar and school hours (in July or between 8pm and 6am). Subtracting these fixed effects from reported cell-level arrests and summing the resulting residual by calendar day produces the (daily) residuals presented above (pegged to July 1st, 2019). The top left panel shows the residuals for male offenders, , and the bottom panel shows residuals for weekends.

## A Appendix Figures

Figure A.1: Reported Crimes and Arrests by Week, By Age of Victim



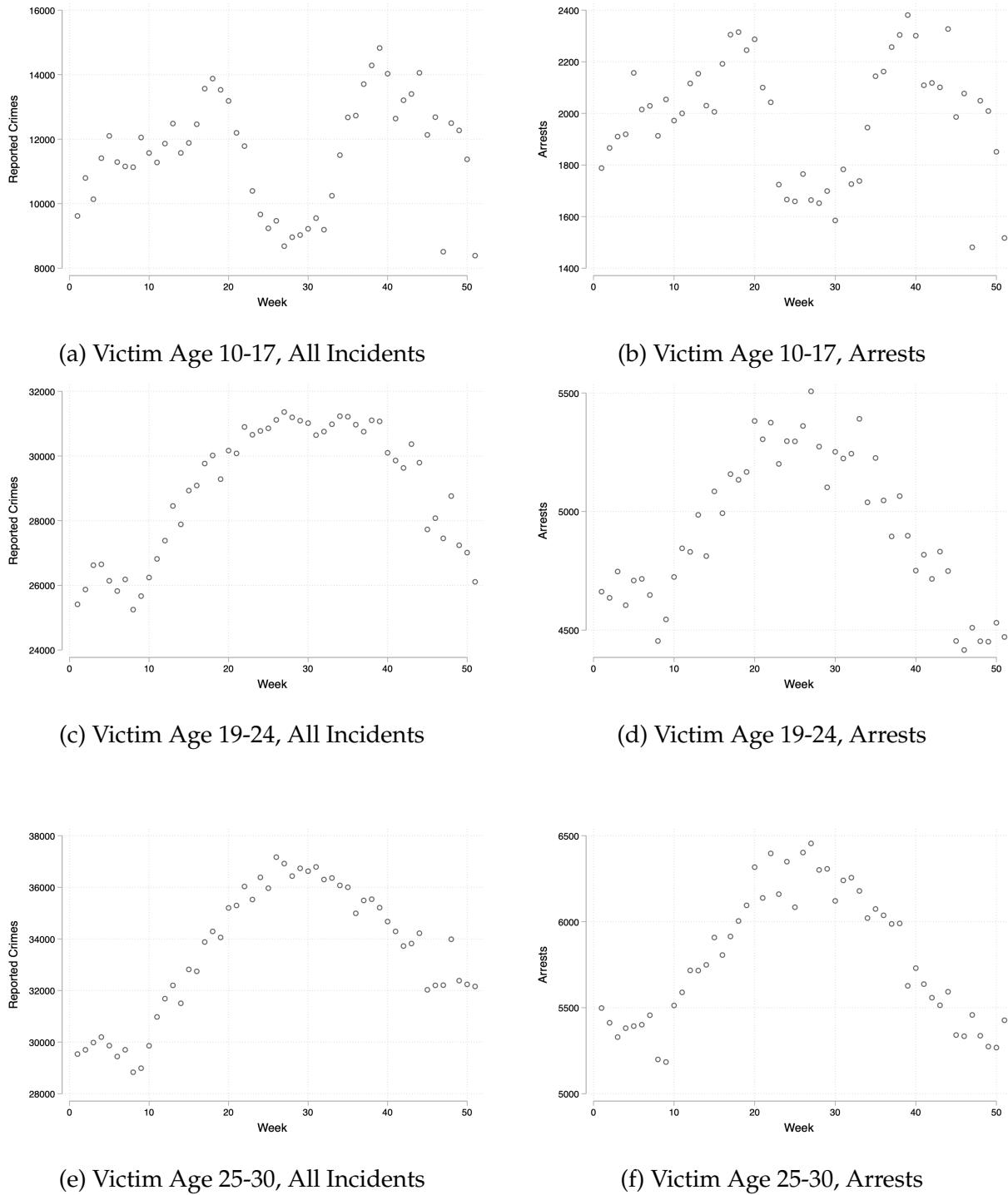
(a) All Incidents



(b) Arrests

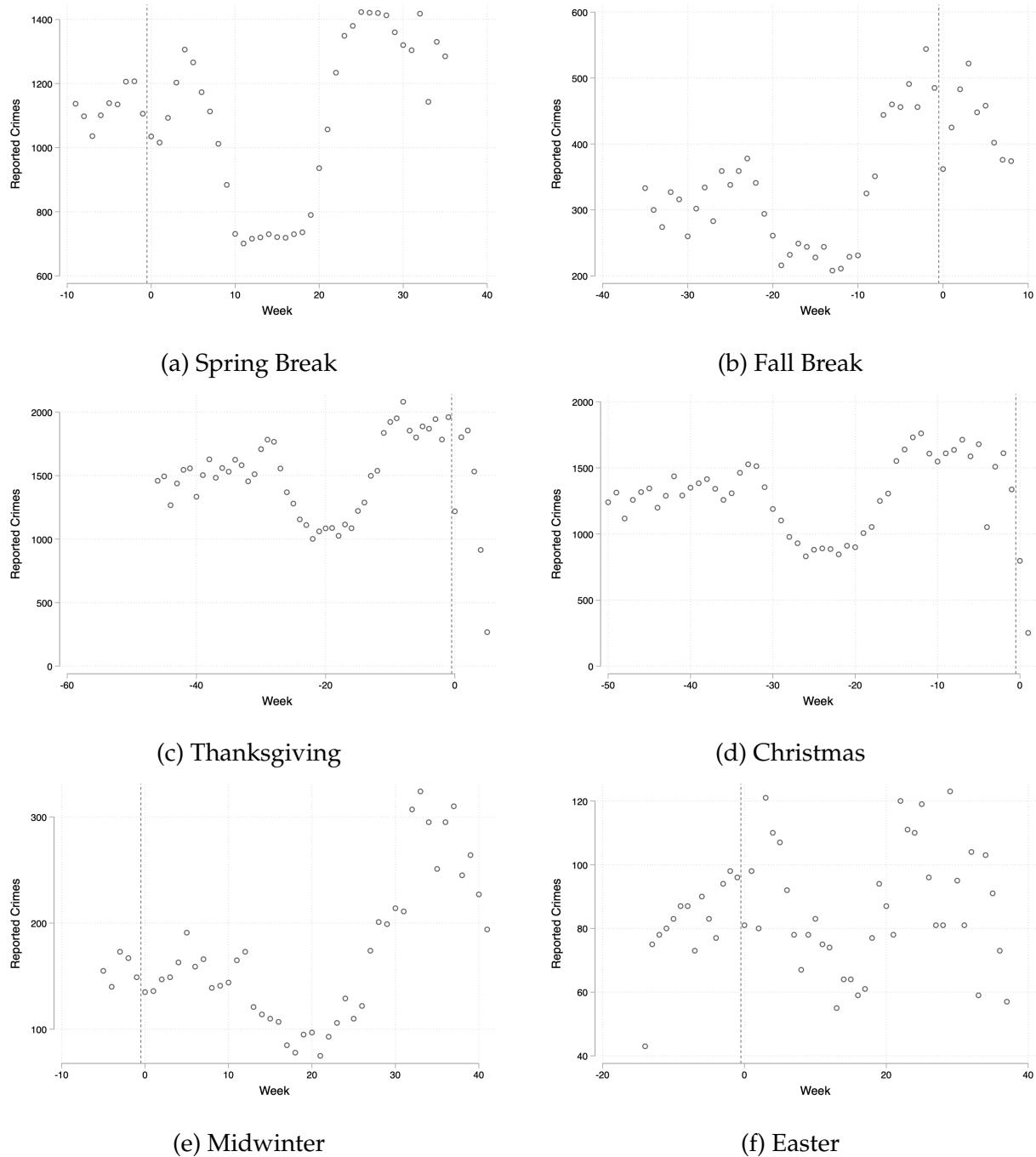
Notes: These figures show the total number of reported crimes by week. Panel A shows the total number of reported crimes, and Panels B shows the total number of arrests and times taken into custody (a subset of the total number of incidents). Data source: 2017-2019 NIBRS. Week 1 starts on the first Monday of the year. Weeks 0, 52, and 53 are excluded.

Figure A.2: Reported Crimes and Arrests by Week, By Age of Victim



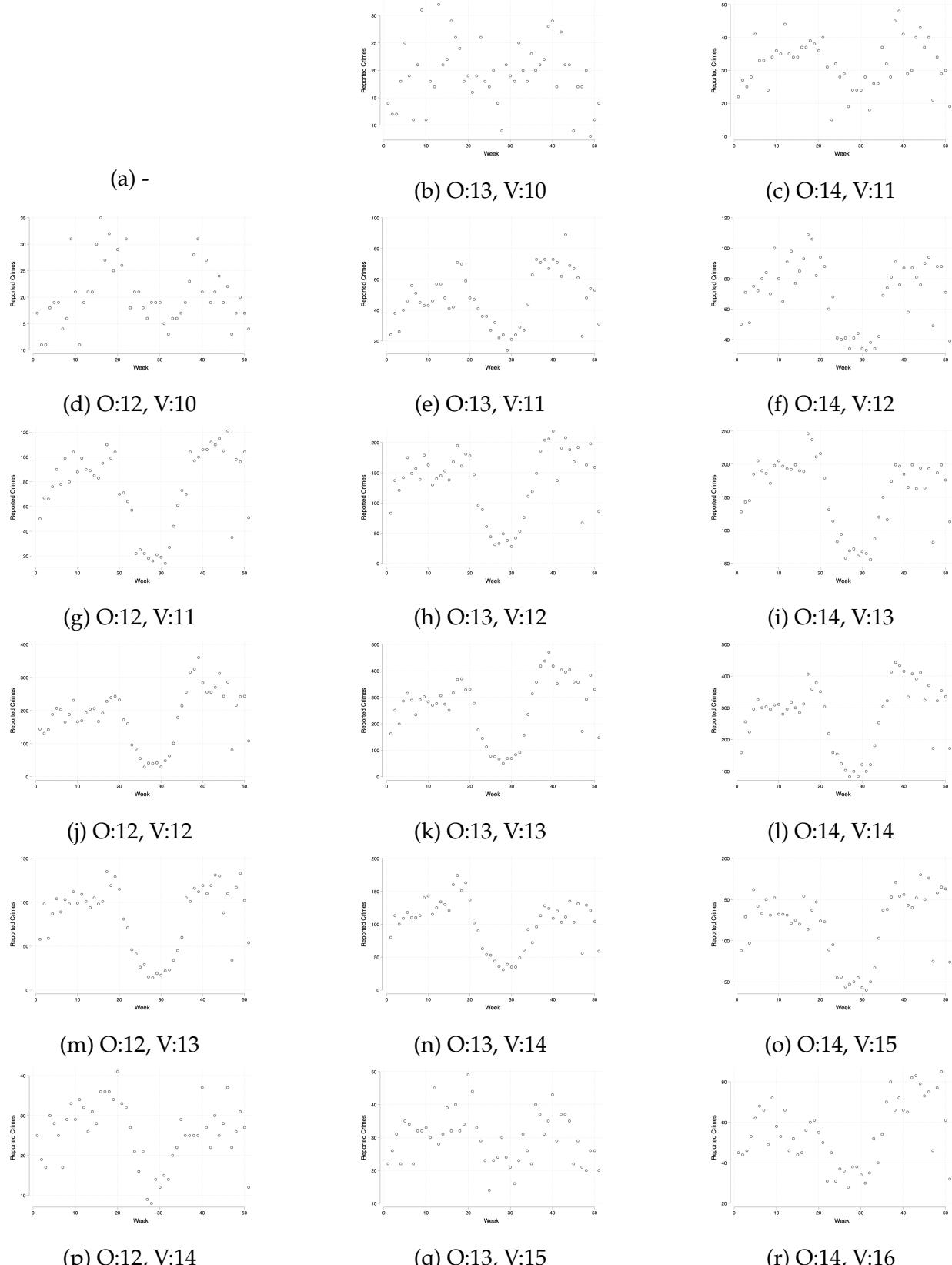
Notes: These figures show the total number of reported crimes by week. Panels A, C, and E show the total number of reported crimes, and Panels B, D, and F show the total number of arrests and times taken into custody (a subset of the total number of incidents). Panels A and B are limited to the offender being 10-17 years old; Panels C and D (E and F) are limited to the victim being 19-24 (25-30) years old. Data source: 2017-2019 NIBRS. Week 1 starts on the first Monday of the year. Weeks 0, 52, and 53 are excluded.

Figure A.3: Crimes by Week Relative to School District Start Date, by Type of Break, 10-17 Years



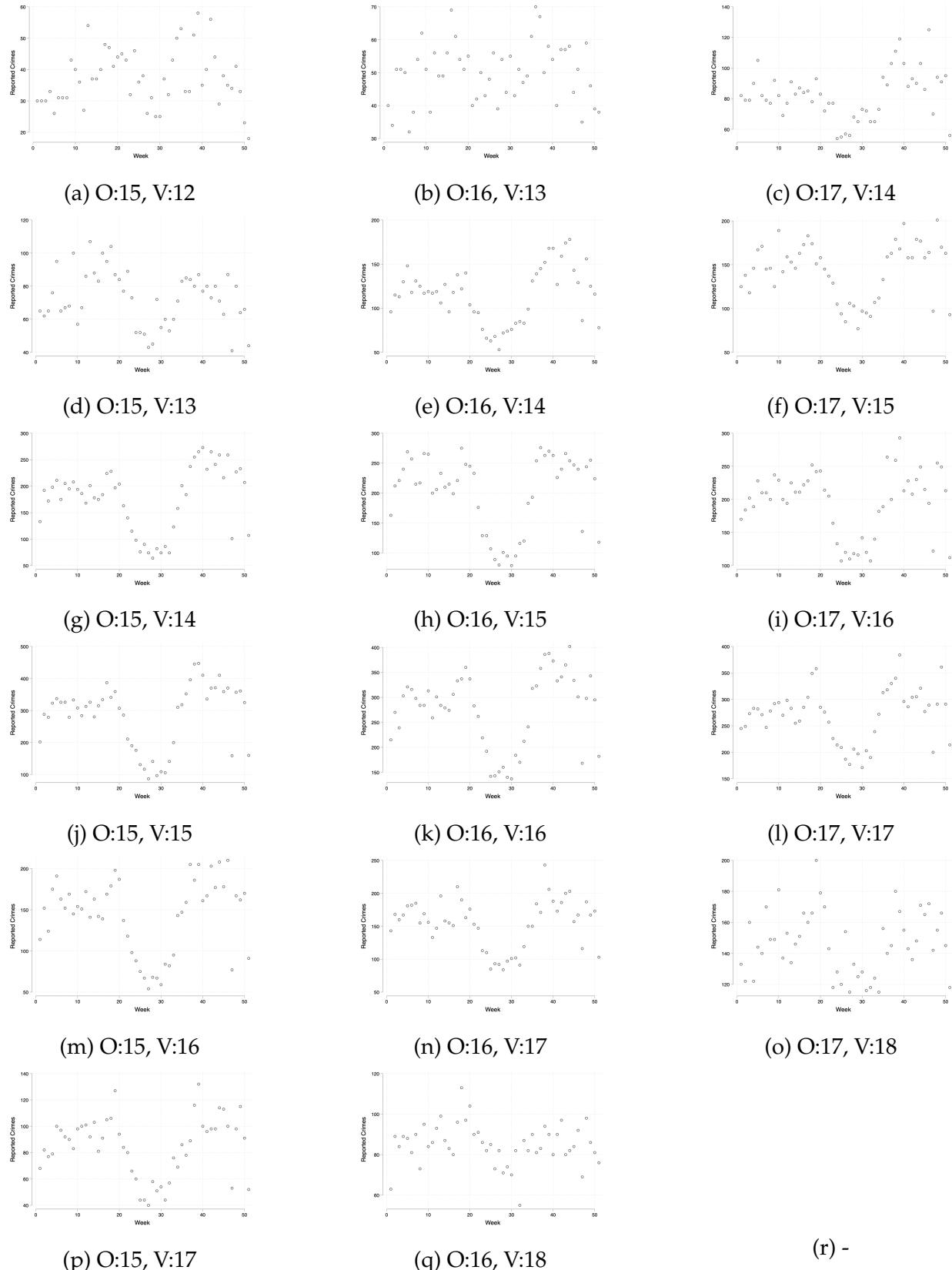
Notes: These figures show a regression discontinuity for the number of crimes by week relative to school district start date for offenders 10-17 years old. Panel A is for spring break; Panel B is for fall break; Panel C is for Thanksgiving; Panel D is for Christmas; Panel E is for midwinter break; and Panel F is for Easter. Data source: 2019 NIBRS. Week 0 is the school district starting date. Only weeks with a balanced panel are shown. A line is drawn at time -0.5.

Figure A.4: Reported Crimes by Week, by Age of Offender and Age of Victim, Offenders Aged 12-14



Notes: These figures show the total number of reported crimes by week for age of first offender (O) and age of first victim (V) pairs. For example, "O: 13, V: 12" means that the offender was 13 and the victim was 12. Offender ages are 12, 13, and 14. The data source is 2017-2019 NIBRS. Week 1 starts on the first Monday of the year. Weeks 0, 52, and 53 are excluded.

Figure A.5: Reported Crimes by Week, by Age of Offender and Age of Victim, Offenders Aged 15-17



Notes: These figures show the total number of reported crimes by week for age of first offender (O) and age of first victim (V) pairs. For example, "O: 15, V: 14" means that the offender was 15 and the victim was 14. Offender ages are 15, 16, and 17. The data source is 2017-2019 NIBRS. Week 1 starts on the first Monday of the year. Weeks 0, 52, and 53 are excluded.