The Effect of COVID-19 on Domestic Crime:

An Analysis of School Closure and Mitigating Effects

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Presented to the Department of Economics at the University of Oregon

March 2022

Abstract

In this paper we estimate the effect of school closures on various crimes with a focus on domestic and child abuse. Additionally, we estimate the effects of family composition variables on the response of these crimes to closures. We find that school closures had a significant effect on the frequency of in-home crime, including child abuse and domestic violence. We also discover that families with persons over 65 in the household, typically grandparents, are less likely to experience the observed crimes. This suggests that the pandemic had a major impact on families and that there are significant mitigating factors through this period.

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I. Introduction

This paper seeks to build upon existing research surrounding the COVID-19 virus and its effect on crime. There is a current wave of literature emerging around this topic as data becomes more available and the effects of the pandemic continue to develop. This paper observes how broad social isolation brought on through school closure altered in-home crimes, including domestic violence and child abuse, and how the changes in the rates of these crimes are affected by family composition.

These types of crimes are the focus of this paper because they are likely to have been most affected negatively by COVID-19. The suspicion is that as more families are forced at home for an extended period of time and experience greater hardship, there may be a greater risk of home violence or other crime. However, with more family presence- in this case we observe grandparents- there ought to be diminishing effects on crimes as we would expect to have more viable witnesses leading to an impact on the number of domestic crimes.

A majority of the literature on this topic focuses on the change in crime rates during closures. This paper looks to contribute to this literature by looking for factors that may additionally affect the closure-induced changes in the rates of the crimes of interest. Factors like median income, employment, population density, and the presence of grandparents in the home may increase or decrease the pressure on parents, partners, and families from school closures, with corresponding effects on the increases in domestic crimes associated with these closures.

This study uses a variety of data sources to be able to look at a range of effects within family homes. Data for crime frequency comes from the National Incident-Based Reporting System (NIBRS) which is run by the FBI. Additionally, much of the mitigating factors come from the American Community Survey (ACS) conducted by the US Census. Lastly, school closure data is gathered through SafeGraph, which records cell phone traffic geographically, which is able to provide an estimate of how many visitors a school received in a given month. This is done by comparing cell phone presence for the given month with the year prior. These sources were determined best fit to approach the topic of interest for this paper as they allow to find greater frequency and reliability.

II. Literature Review

We looked at prior literature concerning domestic violence, its interaction with school shutdowns, and the reporting of crimes in general relating to COVID-19 as well as other economic shocks. These papers show measures taken previously to retrieve data as well as various models which best fit the topic. Additionally, these authors highlight issues that this project runs into as well, including issues on criminal incidents and school closures, and they also provide us with common issues of what could lead to the police reports not matching what we would expect to be the actual counts of domestic violence crimes.

"Family Violence and Football: The Effect of Unexpected Emotional Cues and Violent Behavior"

This paper focused on the relationship between family violence and the wins and losses of professional football teams. The authors, David Card and Gordon B. Dahl, incorporate family violence data from NIBRS with information on Sunday NFL games played by six teams over a 12 year period. From this analysis, Card and Dahl found that upset losses – losses when a team was predicted by four points or more – increase the rate of at-home violence by men against their partners (excluding homosexual partners) by 10%. Card and Dahl also found that upset losses of more important games – such as a playoff game or a game against a rival – led to a larger effect on the rate of violence. Another finding that Card and Dahl had was that there is a significant positive effect of hotter weather on domestic violence. For example, intimate partner violence (IPV) is 8% higher when the maximum temperature is over 80 degrees.

An issue with this paper is that the NIBRS data source participation by police agencies is voluntary and relatively low. Therefore, Card and Dahl had to limit their analysis and sample to only 6 teams and 17 Sunday games during the NFL season. Card and Dahl predicted that if there was more participation in the NIBRS data allowing them to use more teams in their analysis, then the results would be stronger.

"Sheltering in place and domestic violence: Evidence from calls for service during COVID-19"

This paper examines how the increase in family isolation, unemployment, and economic stress affects the rates of domestic violence. The authors, Emily Leslie and Riley Wilson collected data on police calls from 14 large metropolitan cities/areas. Leslie and Wilson found that the pandemic led to a 7.5% increase in police calls reporting domestic violence incidents in March, April, and May. Furthermore, they found that the largest increase in police reports – a 9.7% increase – for domestic violence incidents occurred the first five weeks following March 9th, 2020. Leslie and Wilson compared the social distancing effect on domestic violence to the effect that a hot day has on domestic violence. However, Leslie and Wilson recognize that using police call data is not a perfect measure of domestic violence because not all incidents are reported. For example, according to the National Crime Victimization Survey, only 50% of domestic violence incidents were reported to the police from 2014 to 2018.

This paper used a difference-in-differences model where they compared domestic violence calls in 2020 and 2019 from before and after the ninth week of the year – the week social distancing began in 2020.

“Hidden Violence: How COVID-19 School Closures Reduced the Reporting of Child Maltreatment”

One of the key problems in approaching this study is the problem of reporting. It is largely unknown how the reporting of in-home crime changes with COVID-19, with arguments suggesting opposing trends. This paper attempts to observe how school closure affects domestic violence, and a significant portion of reporting lies on teachers hearing and reporting from their students. One study looks at this issue exactly and helps to establish a sound methodology. In a paper titled “Hidden Violence: How COVID-19 School Closures Reduced the Reporting of Child Maltreatment” authors Francisco Cabrera-Hernandez and Maria Padilla-Romo examine the titular trend in Mexico City. This paper argues that the decline in reporting is not additionally conveying a decrease in child maltreatment, as they employ additional models to parse out seasonal effects and other heterogeneous effects.

To observe a difference in reporting, the authors use a difference-in-difference method. This method observes the change over one time period and sees how the change in crime reports across the time period of interest deviates from the initial time period. For example, in their study, they observe weekly reporting trends for 2020 relative to 2019. The authors found a reduction in child maltreatment reports of 30%, with larger reductions among female victims and in high-poverty areas. This study helps to shed light on the reporting problem that will be faced in this paper. This informed what to expect in terms of reporting when observing crime in the US, and the methods used in the paper also helped to create models for this. While a difference-in-difference model will not be used here, assessing how closure over time affects abuse is important to both papers. We also expect to undershoot out estimates due to lowered reporting rates.

"Police Violence Reduces Civilian Cooperation and Engagement with Law Enforcement"

Another concern for this study in reporting is social movements and changes in the public opinion towards law enforcement that occurred during the time period of interest. One paper out of Harvard examines this issue with the case of George Floyd's murder in May of 2020. This study by authors Desmond Ang et al. observes a significant drop in reporting after the murder and consequently concludes that the relationship that the public has with the police force was negatively impacted.

In order to measure this, the authors use data from ShotSpotter, which is an audio recording system implemented in many cities to better capture the time and location of gunshots. They then use this data against actual reported gunshots to see how the real reporting decreases after their incident of interest. In their results, they found that the national average of calls reporting gunshots went down by 25%, and in some specific cities (Baltimore, New York City) calls dropped by 50%. This effect could potentially skew this paper's findings, though a larger time range will be used in an effort to mitigate this effect.

This study in particular helped to highlight one issue we could not find a practical solution to. Later in this study, graphs of various crimes show certain peaks which could be exacerbated by the current social and political state of the country. However, much of the regressions and other observations helped to parse out the shorter-term effect observed in this study.

With this paper and the one discussed previously, we determined that reporting may be an issue and will more than likely be an issue of under-reporting. In this case, we can reasonably determine that any results found in this topic could be an undervaluing of the true change in crime as a result of COVID-19 and stay-at-home orders.

III. Data

Our school closure data came from the U.S. School Closure & Distancing Learning Database which provided an estimate of how many visitors schools in a given county received in a month. With this data, we are able to see how school closure changed over 2020 and how that affected child, partner, and stranger crimes. We used the 2018 and 2019 American Community Survey to provide estimates of total population, population density, household income, elderly population, and the unemployment rate. This data allows us to see how these factors affect child, partner, and stranger crimes. Lastly, we used data from the National Incident-Based Reporting System which provided detailed incidents of various crimes. From this data, we are able to observe the number of child, partner, and stranger crime cases that occurred in a county in a given month. Put all together, these three data sources will help us observe how school closure, total population, population density, household income, elderly population, and the unemployment rate affect child, partner, and stranger crime.

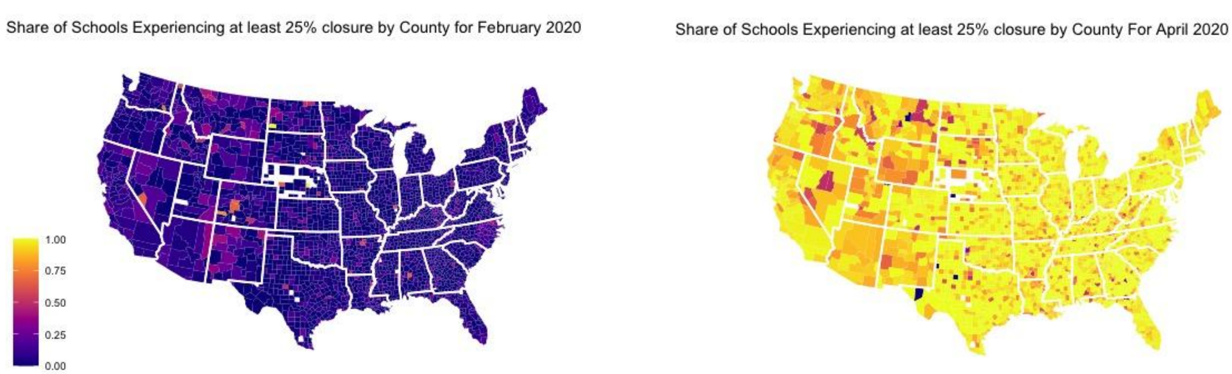
U.S. School Closure & Distance Learning Database (Safe Graph)

We used data from the U.S. School Closure & Distance Learning Database in order to show the relationship between school closure and domestic violence. This data was constructed by Zachary Parolin and Emma K. Lee in order to see where school closure was most common in the United States. To construct the U.S. School Closure & Distance Learning Database, Parolin and Lee used mobile phone data from SafeGraph. SafeGraph uses GPS data on mobile devices in order to study the patterns of foot traffic of places such as businesses and schools. Parolin and Lee measure foot traffic of more than 100,000 schools across the United States. They compare foot traffic data in a given month during 2020 with foot traffic data in the same month during 2019 in order to calculate the year-over-year change of visitors that a school saw. Parolin and

Lee exclude private schools from their analysis which leaves them with data from 80,785 public schools which includes 12,727 school districts. When compared with the number of public schools and school districts in the US according to the National Center for Education Statistics, Parolin and Lee find that their data covers about 82% of public schools and 94% of public school districts.

One major issue with this data is that it doesn't provide the actual percentage change of visitors for a given school in a county. Instead, it provides the percentage of schools that saw at least a 25% decrease in visitors, 50% decrease in visitors, and 75% decrease in visitors in a given county. The below figures are a visual representation of the SafeGraph data, showing the percent of school closures by county for two months of particular interest in 2020.

Figure 1



American Community Survey

Another component of this study looks at children and grandparents specifically. While the NIBRS data offers more individual data on the victim and assailant, we use census data to retrieve county data on the presence of grandparents and children in family homes. The American Community Survey (ACS) data offers variables on the presence of persons over 65 as well as under 18 in a family home, which is defined as two or more people in a household sharing a relationship of birth, marriage, or adoption. While not specific to the individual, this can serve as a probability of having a grandparent in the house when logged in the regression. We expect to observe that a larger presence of grandparents in homes would result in lower cases of domestic abuse. We suspect this because the grandparents would act as a mediator or witness to any spousal or child abuse occurring.

There are problems associated with the use of this data. The U.S. Census Bureau did not conduct the ACS for 2020 or 2021 due to the Covid-19 Pandemic, so the scope of use for this data is in 2019, and 2018 for population density. Consequently, the data cannot be used to observe time-series related trends, only fixed effects. This data is also only at the county level, and it cannot be established that there was a grandparent present in a household that has a reported incident. The variables used from this data will be a likelihood that there was a grandparent present, based on the number of grandparents in family homes for a given county. We also assume that household composition does not change across time, given that we are observing a shorter period of time (2018-2020). Other controls retrieved from the ACS include total population, the total number of households, average income, labor force, and unemployment. Below are summary statistics for the variables used in this paper from the ACS:

Table 1

Type	Number	Mean	Std Dev.	Min	Pct. 25	Pct. 75	Max
Total population	56,522	92,941	255,930	589	11,776	66,846	4,646,630
Total number of households	56,522	35,120	93,487	289	4,603	25,713	1,605,368
Minors in household	56,522	10,882	31,004	33	1,275	7,636	606,059
Elderly people in households	56,522	5,857	14,180	52	915	4,840	269,301
Mean household income	56,522	54,100	13,789	24,623	45,051	60,711	142,299
Total civilian labor force	56,522	47,265	134,087	351	5,118	31,073	2,387,583
Unemployment	56,522	2,336	7,021	0	245	1,564	138,920
Population Density	56,522	86	279	0	7	48	5,249

National Incident-Based Reporting System

One of the primary sources of data we used for our analysis was from the National Incident-Based Reporting System (NIBRS) under the FBI. This data set consists of a large selection of police agencies across the country that volunteer their complete, descriptive lists of crimes each year that detail most characteristics of a criminal incident except for exact location, but we were able to conduct a lot of analysis by compiling reports for each given county included in the data files which amounted to 1,113 counties which reported for their crimes from 2018 to 2020, though there were several states that this set did not span which include Alabama, Alaska, California, Florida, Nebraska, Nevada, New Jersey, New York, North Carolina, and Wyoming.

For each state and a given year, we downloaded the NIBRS data set which includes a file of 26 separate excel sheets for different specifications of a given crime. The files that pertained to our research consisted of six different types of files: agencies, incident, victim, offender, victim-offender relationship, and offense. Through the combination of these files, we created our own dataset that summarizes the types of crime we need with the given county, state, month, and year indexes. The types of crime that we observe for this project include partner crime, child crime, and stranger crime. We specified partner crime to include any physical, verbal, or sexual offense at a residence/home with which the victim is currently or used to be in a romantic relationship with (married, ex-married, boyfriend/girlfriend, ex-boyfriend/ex-girlfriend, and homosexual). Child crime is filtered for physical, verbal, or sexual offenses at a residence/home where the victim is a minor and the relationship to the abuser is child, child of boyfriend/girlfriend, stepchild, or grandchild. The stranger crimes are filtered for physical, verbal, or sexual offenses where the relationship between the offender and victim is unknown or identified as a stranger. See Table 3 to see what specific types of crime we classified for our three groups. We also included additional variables of crimes as a percentage of the population of each county so we can control for population in our regressions.

One of the difficulties associated with this data is its lack of specific location, so we were unable to add in a factor of proximity to the schools that are shutting down and instead are left with the broad spaces covered by each county. This limits our methods because with specific location data we could have added a spatial analysis to account for crimes within given school districts. Below are summary statistics of the types of crime, followed by a table detailing the categories of crimes:

Table 2

Type	Number	Mean	Std Dev.	Min	Pct. 25	Pct. 75	Max
Partner Crime	56,522	47	162	0	2	29	4,474
Child Crime	56,522	51	188	0	2	32	5,967
Stranger Crime	56,522	59	203	0	2	37	5,644
Victim Male	56,522	153	523	0	8	92	14,215
Victim Female	56,522	153	508	0	7	90	12,770
Offender Male	56,522	220	684	0	14	147	18,248
Offender Female	56,522	90	250	0	5	65	5,986
Offender Minor	56,522	22	65	0	1	15	1,317
Offender Adult	56,522	280	958	0	14	165	25,108
Percent Partner	56,522	0.047	0.065	0	0.013	0.061	1.475
Percent Child	56,522	0.052	0.071	0	0.013	0.067	1.476
Percent Stranger	56,522	0.060	0.083	0	0.014	0.078	1.654

Table 3

Crimes against Children	Crimes against Partners	Crimes against Strangers
Simple Assault	Simple Assault	Simple Assault
Fondling	Fondling	Fondling
Rape	Rape	Rape
Homicide	Homicide	Homicide
Statutory Rape	Sexual Assault With An Object	Statutory Rape

Sexual Assault With An Object	Assisting or Promoting Prostitution	Sexual Assault With An Object
Assisting or Promoting Prostitution	Aggravated Assault	Aggravated Assault
Run Away	Kidnapping/Abduction	Prostitution Offenses
Aggravated Assault	Prostitution Offenses	Murder and Nonnegligent Manslaughter
Kidnapping/Abduction	Murder and Nonnegligent Manslaughter	Negligent Manslaughter
Prostitution Offenses	Negligent Manslaughter	Human Trafficking, Commercial Sex Acts
Murder and Nonnegligent Manslaughter	Sodomy	Human Trafficking, Involuntary Servitude
Negligent Manslaughter	Human Trafficking, Commercial Sex Acts	
Sodomy	Human Trafficking, Involuntary Servitude	
Intimidation		
Incest		
Human Trafficking, Commercial Sex Acts		
Human Trafficking, Involuntary Servitude		

IV. Methodology

In order to observe how in-home crime has changed during COVID-19, we employ an array of models focusing on different aspects of crime and their characteristics. To begin, we first look at the effect COVID-19 has on time spent at home, and we observe this in the school closure data.

For our study, we create two new variables. Our first variable, "Minimum Students Home", measures the minimum number of students home due to school closure in a given county. To calculate this, we subtract the variables "share_all_closed_25" from "share_all_closed_50" which gives us the decrease in visitors by 25% to 50% rather than 25% to 100%. We then multiply the values in this interval by .25 to weight it accordingly and then multiply it by total students to give us a value of students that were home in this period. Then we repeat this process by subtracting "share_all_closed_50" from "share_all_closed_75" which gives us the decrease in visitors by 50% to 75% rather than 50% to 100%. Again, we multiply these values by .50 to weight it and then multiply by total students. Since share_all_closed_75 is already an interval from a decrease in visitors by 75% to 100% we just multiply share_all_closed_75 by .75 to weight it and then multiply that number by total students. Adding together all of these values gives us our variable of "Minimum Students Home". This formula is detailed below:

$$\begin{aligned}\text{Minimum Students Home} = {} & 0.75 * \text{share\_all\_closed\_75} * \text{Total Students} + \\ & 0.50 * (\text{share\_all\_closed\_75} - \text{share\_all\_closed\_50}) * \text{Total Students} + \\ & 0.25 * (\text{share\_all\_closed\_50} - \text{share\_all\_closed\_25}) * \text{Total Students}\end{aligned}$$

The second variable we create, "Percent of Schools That Experience 25% Reduction", takes the share_all_closed_25 variable from the U.S. School Closure & Distance Learning Database – which measures the percentage of schools in a county that saw at least a 25%

decrease in visitors from the previous year – and multiplies it by 100. By rescaling this variable to examine how a 1 percent increase in schools that experienced at least 25% decrease in visitors will affect crime, rather than a 100 percent increase in schools that experience at least 25% decrease in visitors.

The two different estimators will be referred to as "Closure Estimator" in the following models. With these new variables, the preliminary model can be created. This first model will be built out further, but serves to give first observations at the school closure effect and certain crimes:

$$\text{Crime} = \beta_0 + \beta_1(\text{Closure Estimator}) + u_i$$

In this model, β_1 can be interpreted as the increase in crime occurrences as a response to a unit/percent increase in the estimator. The empty parentheses preceding the crime variable indicate the different crimes we focus on: child, partner, and stranger. Additionally, we looked at the same regression, with the output variable being crime as a percent of the population. This formula is as follows:

$$\text{PercentCrime} = \beta_0 + \beta_1(\text{Closure Estimator}) + u_i$$

To understand the factors that contribute to crime we regress our closure estimator, population density, household income, households with someone at least 65 years old, total population, unemployment rate, and an interaction term between our closure estimator and our variable for elders in a household.

From our literature review, we learned that days where the maximum temperature is at least 80 degrees Fahrenheit will lead to an 8% increase in intimate partner violence. Additionally, students and teachers typically do not attend school during most of June, July, and August. We include month specific fixed effects to account for these changes.

In this regression, we take the variables from the ACS and control for months by using fixed effects. This keeps the variation across months constant over time. This creates our second model:

$$\text{Crime} = \beta_1(\text{Closure Estimator}) + \beta_2\text{PopDens} + \beta_3\text{HHInc} + \beta_4\text{HH65 Percent} + \beta_5\text{urate} + \beta_6\text{Closure Estimator*HH65 Percent} + \beta_7\text{Population} \mid \text{Month}$$

In this model, β_1 can be interpreted as a 1 unit/percent increase in our closure estimator will lead to a β_1 increase/decrease in crime; β_2 can be interpreted as a 1 percent increase in population density will lead to a β_2 increase/decrease in crime; β_3 can be interpreted as a 1 unit increase in household income will lead to a β_3 increase/decrease in crime; β_4 can be interpreted as a 1 percent increase in households with someone 65 years old will lead to a β_4 increase/decrease in crime; β_5 can be interpreted as a 1 percent increase in the unemployment rate will lead to a β_5 increase/decrease in crime; and β_6 can be interpreted as the interaction coefficient between the at least 25 variable and percentage of households with someone at least 65 years old, which is the effect of elder presence on crime when there is some degree of closure. β_7 represents the change in given crime as a response to a one-unit increase in population.

In the next model, rather than looking at the change in cases of crime, we look at the change in crime as a percentage of population. We then regress with the same variables as in the previous model except for the total population in order to compare. The population variable is excluded because it is already accounted for by manipulating the output crime variable:

$$\text{Percent Crime} = \beta_1(\text{Closure Estimator}) + \beta_2\text{PopDens} + \beta_3\text{HHInc} + \beta_4\text{HH65 Percent} + \beta_5\text{urate} + \beta_6\text{Closure Estimator*HH65 Percent} \mid \text{Month}$$

Lastly, to involve the interaction effect of grandparents and our school closure estimators, we derive our regression results with respect to the school closure estimator involved in the given regression. This lets us utilize the interaction effect to thoroughly estimate the rate of change in each crime with respect to the change in unit of school closure. Our partial derivation is illustrated accordingly:

$$\frac{d \text{ Crime}}{d \text{ Closure Estimator}} = \text{ Closure Estimator} + \beta_6 \text{ HH65 Percent}$$

Then we substitute β_6 with our interaction coefficient to result in:

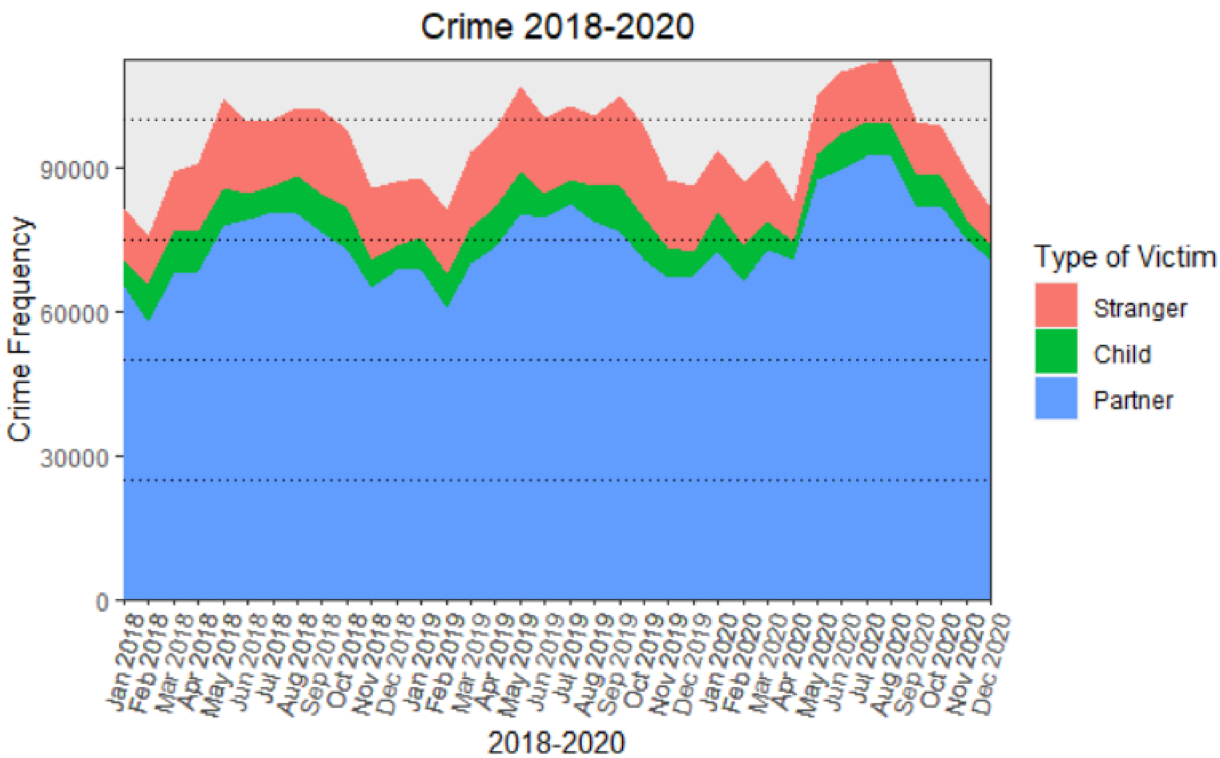
$$\frac{d \text{ Crime}}{d \text{ Closure Estimator}} = \text{ Closure Estimator} + \text{Interaction} * \text{HH65 Percent}$$

"Closure Estimator" and "Interaction" represent the coefficients we find from our regressions. We then replace HH65 Percent with the mean value of this variable from our dataset (shown to be 19.34%) to find the average rate of change in crime with respect to the Closure Estimator.

V. Results

Initially, we wanted to observe the crime data further to anticipate trends that may appear in regressions going forward. The figure below graphs our three categories of crime over time:

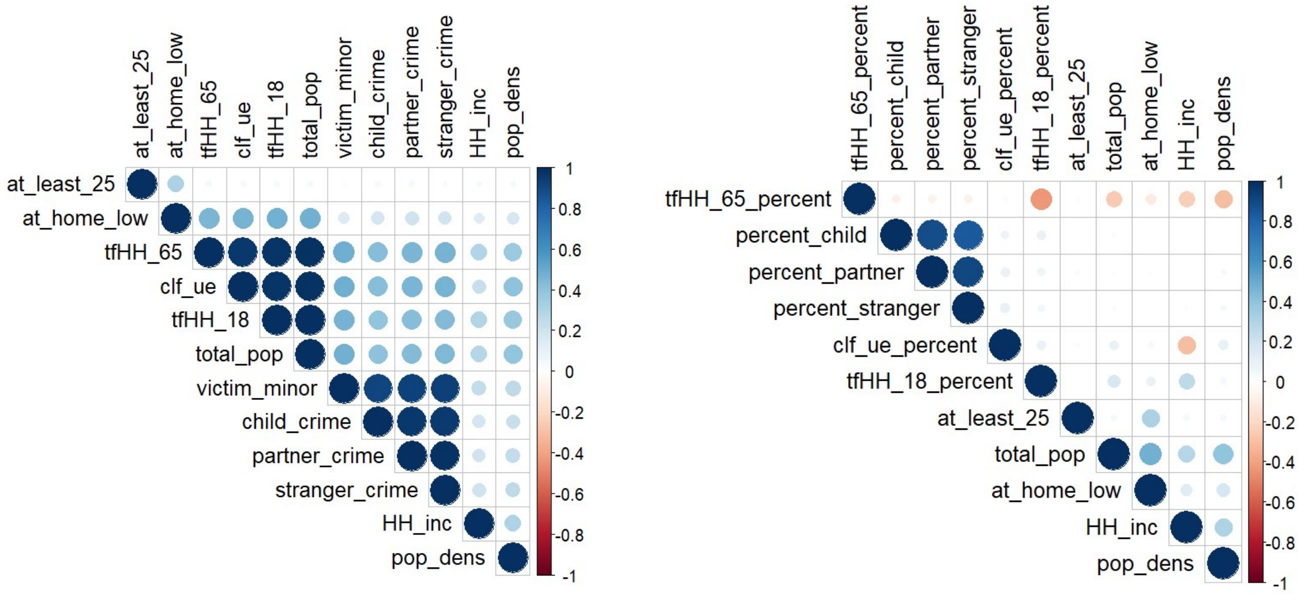
Figure 2



One important observation from this graph is that crime has a seasonal trend: spring and summer months see an increase in crime, with winter months having a lower frequency. The major observation from this figure, though, is a distinct jump in crime around March 2020. This marks when school began closing and COVID-19 cases were beginning to be reported in the US. From the graph, we suspect going forward to see a strong relationship between school closure and crime.

Before building out the models, we also constructed a correlation matrix to observe how strong the correlations are among all the variables we are including in our regression. To understand the graph below, the size of the circles in each box represents the significance of the correlation while the colors indicate the strength of correlation.

Figure 3



Unsurprisingly, the types of crime are highly correlated with one another while maintaining strong significance as we would expect a county with more crimes of one type to be correlated with crimes of other types. Looking at crimes as a percentage of population, there seems to be no noticeable correlations between our school closure estimators and most other variables. However, our crimes observed as whole values have a positive relationship with "Minimum Students Home" as well as most other variables. The percentage of households with a member 65 years old or older (tfHH_65_percent) has a small effect by itself with all types of crime. The remaining variables of total population (total_pop), population density (pop_dens), and the percentage of households with a minor (tfHH_18_percent) all indicate positive coefficients with our observed types of crimes. One cause for concern in this figure is the loss of strength of correlations with crimes as a percent of the population and the variables that we will regress them on, though it is also expected that we will not have a linear relationship between crimes as a percent on variables that are counted as whole values.

Table 4

	Child Crime	Partner Crime	Stranger Crime	Percent Child	Percent Partner	Percent Stranger
(Intercept)	47.50599***	43.06199***	56.03674***	0.05128***	0.04619***	0.05963***
	(0.89476)	(0.77110)	(0.96577)	(0.00034)	(0.00031)	(0.00040)
Share all 25	0.21067***	0.21991***	0.20464***	0.00002*	0.00005***	-0.00000
	(0.02541)	(0.02190)	(0.02743)	(0.00001)	(0.00001)	(0.00001)
R2	0.001	0.002	0.001	0.000	0.001	0.000

	Child Crime	Partner Crime	Stranger Crime	Percent Child	Percent Partner	Percent Stranger
(Intercept)	45.75271***	41.78341***	53.60018***	0.05153***	0.04687***	0.05955***
	(0.78539)	(0.67475)	(0.84668)	(0.00030)	(0.00028)	(0.00035)
Minimum Students Home	0.00400***	0.00375***	0.00445***	0.00000+	0.00000**	0.00000
	(0.00009)	(0.00008)	(0.00009)	(0.00000)	(0.00000)	(0.00000)
R2	0.035	0.042	0.038	0.000	0.000	0.000

This table gives the results from both closure estimators, “Share all 25” and “Minimum Students Home” being independently regressed on “crime”, and “percent crime” for each type of crime we observed.

Both variables exhibit positive effects, increasing instances of all types of crime when the closure estimator increases. When we use the “Share all 25” closure estimator we found that a 1 percentage point increase in counties that had at least 25 percent school closure had the largest effect on partner crime. However, when we use the “Minimum Students Home” closure estimator, we found that an additional student home had the largest effect on stranger crime.

When the output crime variable is a proportion of the population, though, many of the coefficients are insignificant. This may be due to misspecification and that a percentage measurement may not have a linear relationship.

Table 5

	Child Crime	Partner Crime	Stranger Crime	Percent of Child Crime	Percent of Partner Crime	Percent of Stranger Crime
Share all 25	0.54231*	0.57140**	0.35658+	-0.00000	0.00006+	-0.00007+
	(0.17575)	(0.15771)	(0.18209)	(0.00004)	(0.00003)	(0.00003)
Population Denisty	-0.02882***	-0.01682***	-0.01571***	-0.00000***	0.00001***	0.00002***
	(0.00105)	(0.00087)	(0.00123)	(0.00000)	(0.00000)	(0.00000)
Household Income	0.00130***	0.00106***	0.00150***	0.00000**	0.00000***	0.00000***
	(0.00002)	(0.00003)	(0.00003)	(0.00000)	(0.00000)	(0.00000)
Percent of elderly people in households	-3.12877***	-2.73288***	-3.43458***	-0.00135***	-0.00094***	-0.00130***
	(0.10446)	(0.10055)	(0.12382)	(0.00004)	(0.00003)	(0.00005)
Total population	0.00026***	0.00024***	0.00031***			
	(0.00001)	(0.00001)	(0.00001)			
Unemployment Rate	16.14643***	14.75774***	19.73755***	0.00589***	0.00611***	0.00933***
	(0.42949)	(0.40972)	(0.51838)	(0.00028)	(0.00022)	(0.00038)
Interaction	-0.02404**	-0.02450**	-0.01635+	0.00000	-0.00000	0.00000
	(0.00746)	(0.00665)	(0.00765)	(0.00000)	(0.00000)	(0.00000)
R2	0.183	0.209	0.219	0.015	0.017	0.022

This table uses the closure estimator, "Share all 25" which measures the percentage of schools in a given county that have at least 25% fewer visitors from the year prior. The results from this table are consistent with our literature review.

We found that a 1 percentage point increase in counties that experienced at least 25 percent school closure will lead to an increase of 0.54 in child crime cases, 0.57 in partner crime cases, and 0.35 in stranger crime cases. We also found that a 1 percentage point increase in elderly people in households in a given county will lead to a decrease in 3.12 child crime cases, a decrease in 2.73 partner crime cases, and a decrease in 3.43 stranger crime cases. All of these coefficients are statistically significant.

Another notable finding is that a 1 percentage point increase of elderly people in households in a given county will lead to a 0.00135 percentage point decrease in child crime, a .00094 percentage point decrease in partner crime, and a 0.00130 percentage point decrease in stranger crime. All of these coefficients are statistically significant.

Table 6

	Child Crime	Partner Crime	Stranger Crime	Percent of Child Crime	Percent of Partner Crime	Percent of Stranger Crime
Minimum Students Home	-0.00203***	-0.00196***	-0.00383***	-0.00000***	-0.00000***	-0.00000***
	(0.00029)	(0.00027)	(0.00031)	(0.00000)	(0.00000)	(0.00000)
Population Denisty	-0.02798***	-0.01593***	-0.01487***	-0.00000***	0.00001***	0.00002***
	(0.00087)	(0.00070)	(0.00103)	(0.00000)	(0.00000)	(0.00000)
Household Income	0.00129***	0.00105***	0.00148***	0.00000**	0.00000***	0.00000***
	(0.00003)	(0.00003)	(0.00003)	(0.00000)	(0.00000)	(0.00000)
Percent of elderly people in households	-3.61640***	-3.22938***	-3.84652***	-0.00138***	-0.00101***	-0.00133***
	(0.11926)	(0.10663)	(0.13179)	(0.00006)	(0.00005)	(0.00005)
Total population	0.00026***	0.00024***	0.00032***			
	(0.00001)	(0.00001)	(0.00001)			
Unemployment Rate	16.12572***	14.76717***	19.55666***	0.00590***	0.00613***	0.00931***
	(0.44506)	(0.42570)	(0.51435)	(0.00028)	(0.00022)	(0.00038)
Interaction	0.00013***	0.00013***	0.00022***	0.00000***	0.00000***	0.00000***
	(0.00001)	(0.00001)	(0.00002)	(0.00000)	(0.00000)	(0.00000)
R2	0.183	0.209	0.219	0.015	0.017	0.022

This table uses the other closure estimator, “Minimum Students Home” which is a lower bound estimate of the number of students home and shows unexpected results. The regressions indicate that increased closure has a mitigating effect on each type of crime, with significant values in each column. For example, the first cell details that 100 more students home results in roughly two fewer instances of child crime, all else held equal.

Additionally notable, the mitigating effect of grandparents is even more present when using this closure estimator. In the corresponding cell in column four, a one percent increase in the percent of people over 65 in family households results in a 0.00138 percentage point decrease in the percentage of child crime of the population. As a reminder, the mean for “Percent of Child Crime” is 0.053. This implies that there is roughly a 2% decrease in child crime as a proportion of the population when the proportion of grandparents in a household increases by one percent.

Table 7

Table 5 Partial Derivatives	Child Crime	Partner Crime	Stranger Crime	Percent of Child Crime	Percent of Partner Crime	Percent of Stranger Crime
dCrime/dShare all 25	0.0772619696	0.09745338	0.040293174	0	0.00006	-0.00007

This table observes the calculations of the partial derivatives of each crime with respect to Share all 25. Thus each value is representative of the change in each crime with a 1% increase in the percentage of schools that had at least 25% less visitation. Since our interaction terms in Table 5 for crimes as a percent of population were insignificant, this makes the partial derivatives for the percent of crimes less reliable as that was used in the calculation. The rest however are using all significant values meaning that there is a positive relationship between the decrease in school visitation and the allotted crime types.

Table 8

Table 6	Child Crime	Partner Crime	Stranger Crime	Percent of Child Crime	Percent of Partner Crime	Percent of Stranger Crime
dCrime/dMin Students	0.0004848188	0.0005548188	0.0004258472	0	0	0

Similar to Table 7, Table 8 observes the calculations of the partial derivatives of each crime with respect to the minimum number of students home. Thus, for each value, an added student home leads to that many more instances of the given crime that it is associated with. All of these values used in the calculation are statistically significant making these results reliable. We see for all types of crime as a whole value, there is a positive relationship between crime occuring when students are home.

VI. Discussion

When we use the "Share all 25" variable, we found that an increase in schools that had at least a 25% decrease in visitors led to an increase in all crimes of interest. From this, we can conclude that the effect of COVID-19 resulted in an increase in child crime, partner crime, and stranger crime. We did not find this surprising as stay-at-home orders caused people to spend more time at home than they previously had which added additional stress in the home.

Unexpectedly, when we regressed the closure estimator "Minimum Students Home," we found that an increase in students home due to school closure led to a decrease in child crime, partner crime, and stranger crime. This is likely due to the variable "Minimum Students Home" taking the weighted average of the available data, thus including more variance and possibly causing the output variable to show less correlation.

Population density also leads to a decrease in all types of crime. This was unexpected because one would expect an area with a higher population would lead to higher crime. However, a higher population density could lead to less privacy which could cause less crimes to be committed. On the other hand, total population had a significant positive coefficient, which was unsurprising.

When regressing household income on the various types of crime, we found unexpected results. We found that an increase in household income leads to an increase in child crime, partner crime, and stranger crime. We expected the opposite effect – higher household income, fewer cases of crime – to occur. We expected the opposite effect because a higher household income would likely decrease the amount of stress in a household. From the "Share all 25" variable and the unemployment rate, we learned that higher stress levels lead to more domestic abuse. However, from our household income coefficient, it appears the opposite effect is occurring.

From all of our regressions, we found that an increase in the percent of elder persons in a household for a given county leads to a decrease in cases for all types of crime. We expected this result because a household with an elderly person is less likely to experience child crime, partner crime, and stranger crime.

The interaction term was intended to describe a specific "grandparent effect" during times of school closure. This effect was observed as expected in Table 5, showing a reduction in instances of crime where there are more elders during times of school closure. While the effect was more muted than the individual term for elders, this still accounts for the closure effect. In Table 6, we again saw unexpected results, with the presence of elders increasing instances of various crimes. However, when a partial derivative was done to parse out the closure effect, the coefficient became positive, fitting with our expectations.

Lastly, after regressing the unemployment rate on the three different types of crime we found that an increase in the unemployment rate would lead to an increase in cases of child crime, partner crime, and stranger crime. This finding is not surprising because an increased unemployment rate could cause increased stress in households. This along with the closure estimators, allow us to conclude that higher rates of stress in the household will lead to increased crime.

VII. Conclusion

The initial results as well other literature on the topic lead us to conclude that there is a relationship between school closure and instances of domestic abuse. When children are not able to attend school, they of course spend more time at home and are consequently at a higher risk of domestic abuse. Additionally, closures create more stress for families with crowding and having to sort out child care. Even beyond this, there are economic shocks and conditions that are also brought on by COVID-19 which we assume are largely accounted for with our unemployment variable. These effects of school closures are best reflected in the regressions from Table 5. From this study alone, the ideal policy is to keep schools open. However, school closure occurred in response to COVID-19 as an effort to contain the harm from the deadly disease. Measuring the costs and benefits of such policy going forward are beyond the scope of this study, though, these additional consequences of the pandemic are important.

Additionally, the regressions revealed great insight into various family characteristics and how they can either mitigate or worsen the issue of abuse in the home. The “grandparent effect” was the most interesting, except for the unemployment rate which was expected to have a large effect. This discovery helps to expand on other literature by observing a strong mitigating factor and suggesting families which have a larger presence of extended relatives (specifically grandparents) are likely to have healthier homes and are at less risk of in-home abuse. This is an important finding because it illuminates how family dynamics and composition may adversely disposition families to be at greater risk of domestic crime. Cultures that commonly have grandparents as a part of the household may see less abuse and thus a “healthier” household. This would be an interesting specification for further study.

One of the issues emphasized and addressed by other studies is reporting, and that the reporting of the crimes of interest has declined during COVID-19. This could also mean that estimates and results found in this study undershoot the reality. Conservative closure estimators used in this study also contribute to possible underestimates.

The findings from this research paper speak to an important problem in the US specifically, though other studies find similar results in other parts of the world. The results here also suggest one possible solution to in-home abuse: increased support for schooling and after-school programs to support children in staying out of the house and engaged elsewhere. Additionally, in tackling such sensitive crimes as domestic abuse, officers and support systems could observe families which may be at greater risk of experiencing abuse through factors such as unemployment, household income, and family composition.

VIII. References

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