COVID-19 and crime: Analysis of crime dynamics amidst social distancing protocols

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Abstract

In response to the pandemic in early 2020, cities implemented states of emergency and stay at home orders to reduce virus spread. Changes in social dynamics due to local restrictions impacted human behavior and led to a shift in crime dynamics. We analyze shifts in crime types by comparing crimes before the implementation of stay at home orders and the time period shortly after these orders were put in place across three cities. We find consistent changes across Chicago, Baltimore, and Baton Rouge with significant declines in total crimes during the time period immediately following stay at home orders. The starkest differences occurred in Chicago, but in all three cities the crime types contributing to these declines were related to property crime rather than interpersonal.

Introduction

Crime is a major public concern in the United States. Gun violence leads to the deaths of 36,000 individuals and the non-fatal injuries of 85,000 others [2]. Other crime types can produce property damage, trauma for victims, and fractures in community trust [12]. Across the five major crime types (personal, property, inchoate, statutory and financial), some rely on regular interpersonal interactions and social dynamics [4].

In early 2020, COVID-19 emerged in the United States and case numbers quickly grew across the country. In response to the pandemic, many cities implemented a variety of mitigation policies to minimize spread. A major strategy for preventing viral spread focuses on reducing contacts between individuals [5]. Implementing these types of policies resulted in drastic changes in the behaviors of citizens. Because crime is associated with human behavior, many have questioned how reductions in human contact have changed the dynamics of crimes across the country [1, 6, 7, 9, 13, 14, 17].

In a pandemic which strains health care resources, collateral mortality may increase, due to the inability of the health care system to respond as effectively to crime-derived injuries [15]. Evaluating the impact of the pandemic on crime in a rigorous manner can assess the potential for significant changes in crime-derived mortality to change.

We test whether there are significant differences in the crime dynamics across three cities when comparing the time periods pre- and post-establishment of the stay at home orders. Our main focus is Chicago, Illinois, as it has experienced high rates of both COVID-19 and crime. We then compare these results to Baltimore, Maryland, and Baton Rouge, Louisiana to determine whether similar patterns exist across the three differing cities (Figure 1). We hypothesize that changes in crime dynamics in all three cities in response to the implementation of stay at home orders are not uniform across all crime types and that there are differences between crimes associated with property (e.g. burglary, robbery, theft) and those involving interpersonal interactions (e.g. assault, criminal sexual assault, sex offense).

Materials and Methods

Data

All data and code files used in this analysis are available through GitHub at <https://github.com/shelbymscott/COVIDandCrime>.

Chicago Data

The Chicago City Data Portal provides crime reports from 2001-present (3). Data are extracted from the CLEAR (Citizen Law Enforcement Analysis and Reporting) system. The information from this dataset used for this analysis includes the date, primary type, and description, but a number of other items are available. We isolated the crimes which occurred from January 1, 2020 through April 4, 2020, which gave data from before the onset of the pandemic (01/01/2020 - 03/08/2020), during the state of emergency (03/09/2020 - 03/20/2020), and after the stay at home order was put in place (03/21/2020 - 04/04/2020) for temporal comparisons. There are 32 different crime types available, but for this analysis we choose 20 of the crime types including:

- Total Crimes
- Gun Crimes (pulled from crime descriptions that included firearm use)
- Arson
- Assault
- Battery
- Burglary
- Criminal Damage
- Criminal Sexual Assault
- Criminal Trespass
- Deceptive Practice
- Homicide
- Interference with Public Officer
- Motor Vehicle Theft
- Narcotics

• Offense Involving Children	56
• Other Offense	57
• Public Peace Violation	58
• Robbery	59
• Sex Offense	60
• Theft	61
• Weapons Violation	62

These crime types were chosen because they composed a high proportion of total crimes or were present in the Baltimore or Baton Rouge datasets for appropriate comparison. Those crime types excluded due to low numbers were: concealed carry license violations, gambling, human trafficking, intimidation, kidnapping, liquor law violations, obscenity, other narcotics violations, prostitution, public indecency, and stalking. We determined whether the crime types should be included based on if it comprised $\geq 0.2\%$ of total crimes. This number was found by determining the lowest percentage from the Baltimore and Baton Rouge datasets and only including those crimes which exceeded this amount.

Baltimore Data 72

Baltimore, Maryland has Victim Based Crime data available for public download (10). The data are preliminary and therefore may be subject to change (10). The data provided includes a number of different options from which to choose. The relevant information we use includes the date of the crime and the crime type. We isolate those crime types which occurred from the beginning of the year (1/1/20) to when the stay at home order was put in place (3/29/20) and the two weeks following the implementation (3/30/20 - 4/13/20). The 11 crime types we use include:

• Total Crimes	80
• Gun Crimes (determined by finding those crimes which involved a firearm as a weapon)	81
• Assault	83
• Arson	84
• Auto Theft	85
• Burglary	86
• Homicide	87
• Larceny	88
• Rape	89
• Robbery	90
• Shooting	91

Baton Rouge Data

Crimes reported in Baton Rouge are handled by the Baton Rouge Police Department and are publicly available (11). The data are pulled from police reports using automatic statistical reporting, which can lead to some errors (11). We obtained the dates and crime types from the extensive dataset and parse for the time period from the beginning of the year to when the stay at home order was put in place (1/1/20 - 3/21/20) and the two weeks following the stay at home order (3/22/20 - 4/5/20). The 15 crime types analyzed include:

- Total Crimes
- Assault
- Battery
- Burglary
- Criminal Damage
- Firearm
- Homicide
- Juvenile
- Narcotics
- Nuisance
- Other
- Robbery
- Sexual Assault
- Theft
- Vice.

t-Test Analysis

In order to determine whether the differences seen in crime dynamics are significant or not, we performed numerous *t*-tests that compared whether different years and time periods differed significantly (8). Because we were performing a number of statistical tests simultaneously, we used the Bonferroni correction to be sure that spurious positives were not included (16). The Bonferroni correction sets the α value for the entire set of n comparisons equal to α^* by taking:

$$\alpha^* = \frac{\alpha}{n}.$$

Formally, given n tests T_i for hypotheses H_i ($1 \leq i \leq n$) under the assumption H_0 that all hypotheses H_i are false, and if the individual test critical values are $\leq \alpha/n$, then the experiment-wide critical value is $\leq \alpha$. In equation form, if:

$$P(T_i \text{ passes} | H_0) \leq \frac{\alpha}{n}$$

for $1 \leq i \leq n$, then

$$P(\text{some } T_i \text{ passes} | H_0) \leq \alpha,$$

which follows from the Bonferroni inequalities.

There were t -tests performed on the datasets in order to determine whether what has been observed in 2020 is significantly different behavior from other years. These included:

- Year in year tests to determine whether the 2020 observed behavior differs from what we would have expected from previous years (Table 1).
- Within year analysis to determine whether the behavior before pandemic response and after the stay at home orders were put in place differ from one another (Table 2).
- Time period comparisons over Baltimore and Baton Rouge to determine whether the patterns seen in response to COVID in Chicago are consistent across numerous cities (Table 2).
- Comparison tests with past years to determine whether the observed behavior is due to seasonality or differing temporal dynamics during the pandemic (Tables S1-S9).

Results

Comparing January through March Chicago crime data (early 2020) to the same time period in each of the three previous years determines which crime types in 2020 are significantly different [3]. The results (Table 1) show that between 2019 and 2020, there were decreases in total crimes, burglaries, narcotics, other offenses, and thefts. Between 2018 and 2020, total crimes, burglaries, criminal damages, criminal trespasses, narcotics, other offenses, robberies, and thefts all decreased, while weapons violations increased. Between 2017 and 2020, total crimes, burglaries, criminal damages, criminal trespasses, other offenses, public peace violations, robberies, and thefts all decreased, while weapons violations increased.

To determine whether there were significant differences in crime between time periods, we performed a series of t -tests [8, 16]. While Chicago had three distinct time periods: pre-COVID, a state of emergency, and a stay at home order, the results from the state of emergency were not as stark as comparisons between the time period before the stay at home order was implemented and the two weeks after implementation (see supplementary text and Tables S1-S9). Total crimes, assaults, burglaries, criminal sexual assaults, criminal trespasses, interference with public officers, narcotics, other offenses, robberies, and thefts each had significant decreases from the time period before the stay at home order was put in place to the two weeks following implementation (Table 2).

In order to determine whether similar patterns have been observed in other cities, we test victim-based crime data from Baltimore, before the stay at home order was put in place and two weeks after implementation (Table 2) [10]. We find that total crimes, auto thefts, burglaries, and larceny all showed significant declines between the two time periods (Fig 2c, 2d).

As a further comparison to a smaller population city with different demographics, crime data from Baton Rouge were analyzed (Table 2) [11]. We find that total crimes, narcotics, and other crimes all decreased significantly after the stay at home order was put in place (Fig 2e, 2f).

(a) Chicago total crimes from 01/01/20 - 04/04/20.

(b) Baltimore total crimes from 01/01/20 - 04/13/20.

(c) Baton Rouge total crimes from 01/01/20 - 04/05/20.

Fig 1. The total crime trends seen in Chicago, Baltimore, and Baton Rouge from the beginning of the year through the end of our study period. Each point is the total number of crimes observed on that day. The vertical line represents the day when the stay at home order was implemented for each city.

(a) Chicago Narcotics in 2020. (b) Chicago Theft in 2020.

(c) Baltimore Auto Thefts in 2020. (d) Baltimore Larcenies in 2020.

(e) Baton Rouge Narcotics in 2020. (f) Baton Rouge Other Crimes in 2020.

Fig 2. Example crime types across the three cities that showed significant differences during the time period before stay at home orders were put in place and after they were implemented. Each dot represents the total number of that crime type which occurred daily. The vertical line represents when the stay at home order was put in place for each city. Scatter plots of all other crime types showing significant declines are available in Figure S2.

Early 2019 Dataset (μ, σ)	Early 2020 Dataset (μ, σ)	p-value	Direction of Change
Total Crimes (650, 84.3)	Total Crimes (575, 90.6)	7.45×10^{-7}	-
Gun Crimes (33.6, 9.37)	Gun Crimes (36.4, 9.38)	0.038	+
Arson (0.872, 0.845)	Arson (0.884, 1.07)	0.933	-
Assault (50.8, 9.89)	Assault (47.4, 8.02)	0.010	-
Battery (122, 22.5)	Battery (115, 21.7)	0.033	-
Burglary (23.7, 7.37)	Burglary (20.6, 5.16)	8.53×10^{-4}	-
Criminal Damage (61.7, 13.8)	Criminal Damage (59.1, 12.4)	0.167	-
Criminal Sexual Assault (3.81, 2.44)	Criminal Sexual Assault (3.73, 2.47)	0.818	-
Criminal Trespass (17.5, 5.02)	Criminal Trespass (16.1, 5.70)	0.076	-
Homicide (0.989, 1.05)	Homicide (1.08, 1.03)	0.534	+
Interference with Public Officer (3.40, 1.65)	Interference with Public Officer (3.32, 2.19)	0.755	-
Narcotics (44.1, 11.0)	Narcotics (31.0, 13.6)	8.41×10^{-12}	-
Other Offense (47.8, 9.80)	Other Offense (39.4, 9.98)	2.89×10^{-8}	-
Public Peace Violation (3.81, 2.18)	Public Peace Violation (2.87, 2.06)	0.003	-
Robbery (18.4, 5.59)	Robbery (20.4, 6.11)	0.019	+
Sex Offense (3.28, 2.37)	Sex Offense (2.78, 1.65)	0.095	-
Theft (149, 23.7)	Theft (130, 28.9)	1.09×10^{-6}	-
Weapons Violation (14.5, 5.93)	Weapons Violation (15.6, 5.80)	0.186	+
Early 2018 Dataset	Early 2020 Dataset		
Total Crimes (655, 65.2)	Total Crimes (575, 90.6)	7.63×10^{-11}	-
Gun Crimes (35.1, 7.99)	Gun Crimes (36.4, 9.38)	0.301	+
Arson (0.787, 0.914)	Arson (0.884, 1.07)	0.504	+
Assault (48.7, 9.40)	Assault (47.4, 8.02)	0.295	-
Battery (119, 19.9)	Battery (115, 21.7)	0.137	-
Burglary (27.6, 6.31)	Burglary (20.6, 5.16)	1.14×10^{-14}	-
Criminal Damage (66.2, 14.8)	Criminal Damage (59.1, 12.4)	4.00×10^{-4}	-
Criminal Sexual Assault (3.74, 2.67)	Criminal Sexual Assault (3.73, 2.47)	0.961	+
Criminal Trespass (19.0, 3.78)	Criminal Trespass (16.1, 5.70)	5.32×10^{-5}	-
Homicide (1.30, 1.18)	Homicide (1.08, 1.05)	0.188	-
Interference with Public Officer (3.30, 1.75)	Interference with Public Officer (3.32, 2.19)	0.951	+
Narcotics (37.3, 9.65)	Narcotics (31.0, 13.6)	3.66×10^{-4}	-
Other Offense (45.4, 7.94)	Other Offense (39.4, 9.98)	1.11×10^{-5}	-
Public Peace Violation (3.22, 1.79)	Public Peace Violation (2.87, 2.06)	0.214	-
Robbery (25.1, 6.38)	Robbery (20.4, 6.11)	7.45×10^{-7}	-
Sex Offense (2.61, 3.23)	Sex Offense (2.78, 1.65)	0.644	+
Theft (150, 21.1)	Theft (130, 28.9)	1.19×10^{-7}	-
Weapons Violation (12.1, 4.37)	Weapons Violation (15.6, 5.80)	7.84×10^{-6}	+
Early 2017 Dataset	Early 2020 Dataset		
Total Crimes (686, 74.7)	Total Crimes (575, 90.6)	7.48×10^{-17}	-
Gun Crimes (37.7, 8.86)	Gun Crimes (36.4, 9.38)	0.336	-
Arson (1.21, 1.15)	Arson (0.884, 1.07)	0.044	-
Assault (46.4, 8.24)	Assault (47.4, 8.02)	0.386	+
Battery (121, 19.6)	Battery (115, 21.7)	0.037	-
Burglary (35.5, 10.6)	Burglary (20.6, 5.16)	6.24×10^{-26}	-
Criminal Damage (74.8, 14.1)	Criminal Damage (59.1, 12.4)	6.27×10^{-14}	-
Criminal Sexual Assault (4.07, 3.56)	Criminal Sexual Assault (3.73, 2.47)	0.436	-
Criminal Trespass (18.5, 4.54)	Criminal Trespass (16.1, 5.70)	0.002	-
Homicide (1.65, 1.66)	Homicide (1.08, 1.04)	0.006	-
Interference with Public Officer (2.77, 1.47)	Interference with Public Officer (3.32, 2.19)	0.044	+
Narcotics (33.9, 8.77)	Narcotics (31.0, 13.6)	0.091	-
Other Offense (49.9, 8.96)	Other Offense (39.4, 9.98)	1.41×10^{-12}	-
Public Peace Violation (3.87, 2.12)	Public Peace Violation (2.87, 2.06)	0.001	-
Robbery (29.5, 7.27)	Robbery (20.4, 6.11)	4.86×10^{-17}	-
Sex Offense (2.67, 3.78)	Sex Offense (2.78, 1.65)	0.798	+
Theft (154, 21.4)	Theft (130, 28.9)	5.99×10^{-10}	-
Weapons Violation (10.8, 4.23)	Weapons Violation (15.6, 5.80)	7.26×10^{-10}	+

Table 1. Comparisons of each Chicago crime type in the first three months 2019, 2018, and 2017 compared to crime types in the same time period of 2020. The degrees of freedom for these analyses are 179 and $\alpha = .05$ is adjusted after Bonferonni correction (with $n = 18$) to $\alpha = 0.0027$. Bolded crime types show significant differences between years.

Crime Types Pre-Stay at Home Orders (μ, σ)	Crime Types Post Stay at Home Orders (μ, σ)	p-value	Direction of Change
Chicago			
Total Crimes (606, 59.4)	Total Crimes (415, 47.8)	4.61×10^{-20}	-
Gun Crimes (37.1, 9.47)	Gun Crimes (33.1, 8.42)	0.139	-
Arson (0.863, 1.09)	Arson (1.00, 1.00)	0.651	+
Assault (48.9, 7.28)	Assault (39.4, 7.14)	1.07×10^{-5}	-
Battery (117, 21.7)	Battery (100, 15.15)	0.004	-
Burglary (21.4, 5.08)	Burglary (16.5, 3.52)	6.89×10^{-4}	-
Criminal Damage (59.6, 12.5)	Criminal Damage (56.5, 11.5)	0.375	-
Criminal Sexual Assault (4.09, 2.50)	Criminal Sexual Assault (1.80, 1.08)	7.76×10^{-4}	-
Criminal Trespass (17.5, 5.08)	Criminal Trespass (8.73, 2.05)	3.38×10^{-9}	-
Homicide (1.15, 1.08)	Homicide (0.733, 0.704)	0.155	-
Interference with Public Officer (3.89, 1.89)	Interference with Public Officer (0.267, 0.458)	7.46×10^{-11}	-
Narcotics (35.9, 8.07)	Narcotics (5.00, 2.56)	7.09×10^{-26}	-
Other Offense (42.2, 8.15)	Other Offense (24.8, 4.54)	3.27×10^{-12}	-
Public Peace Violation (3.14, 2.11)	Public Peace Violation (1.47, 0.916)	0.003	-
Robbery (21.3, 5.88)	Robbery (15.8, 5.28)	0.001	-
Sex Offense (2.91, 1.65)	Sex Offense (2.07, 1.49)	0.067	-
Theft (139, 21.3)	Theft (82.0, 11.0)	1.83×10^{-16}	-
Weapons Violation (15.8, 6.02)	Weapons Violation (14.3, 4.42)	0.339	-
Baltimore			
Total Crimes (103, 15.4)	Total Crimes (76.3, 12.4)	6.39×10^{-9}	-
Gun Crimes (12.8, 6.70)	Gun Crimes (11.1, 6.21)	0.359	-
Assault (33.2, 7.84)	Assault (28.3, 6.74)	0.024	-
Arson (0.216, 0.441)	Arson (0.133, 0.352)	0.493	-
Auto Theft (8.85, 2.68)	Auto Theft (6.20, 2.70)	6.01×10^{-4}	-
Burglary (11.4, 4.07)	Burglary (8.07, 2.52)	0.003	-
Homicide (0.761, 1.13)	Homicide (0.933, 0.799)	0.575	+
Larceny (34.3, 8.83)	Larceny (22.3, 4.68)	1.24×10^{-6}	-
Rape (0.511, 0.773)	Rape (0.333, 0.488)	0.391	-
Robbery (12.1, 4.30)	Robbery (8.73, 4.64)	0.007	-
Shooting (1.49, 1.68)	Shooting (1.33, 1.35)	0.735	-
Baton Rouge			
Total Crimes (113, 20.0)	Total Crimes (87.7, 15.8)	1.42×10^{-5}	-
Assault (6.45, 3.03)	Assault (5.40, 1.84)	0.198	-
Battery (9.84, 4.38)	Battery (7.00, 1.96)	0.016	-
Burglary (13.7, 5.75)	Burglary (12.1, 4.40)	0.296	-
Criminal Damage (9.03, 3.59)	Criminal Damage (10.0, 3.82)	0.342	+
Firearm (5.21, 3.82)	Firearm (4.53, 2.59)	0.511	-
Homicide (1.20, 1.24)	Homicide (1.53, 0.916)	0.324	+
Juvenile (1.13, 1.27)	Juvenile (0.867, 0.834)	0.450	-
Narcotics (9.23, 5.97)	Narcotics (4.40, 2.72)	0.003	-
Nuisance (1.78, 1.26)	Nuisance (1.33, 1.72)	0.245	-
Other (23.4, 8.94)	Other (13.7, 6.01)	1.06×10^{-4}	-
Robbery (1.31, 1.23)	Robbery (1.27, 1.44)	0.898	-
Sexual Assault (0.512, 0.675)	Sexual Assault (0.333, 0.488)	0.330	-
Theft (29.3, 7.39)	Theft (24.7, 7.47)	0.028	-
Vice (0.575, 0.708)	Vice (0.600, 0.910)	0.905	+

Table 2. Comparisons of the time period before the stay at home order was put in place and the two weeks after it was put in place in Chicago, Baltimore, and Baton Rouge. The observed time period for the stay at home order spans from 03/21/2020 - 04/04/2020 in Chicago. The degrees of freedom for these analyses are 89 and $\alpha = .05$ is adjusted after Bonferonni correction (with $n = 18$) to $\alpha = 0.0027$. The two weeks after Baltimore's stay at home period span from 03/30/20 - 04/13/20. The degrees of freedom for these analyses are 101 and $\alpha = .05$ is adjusted after Bonferonni correction (with $n = 11$) to $\alpha = 0.0045$. The two weeks after Baton Rouge's stay at home order span from 03/22/20 - 04/05/20. The degrees of freedom for these analyses are 93 and $\alpha = .05$ is adjusted after Bonferonni correction (with $n = 15$) to $\alpha = 0.0033$.

Discussion and Conclusions

The analysis of crime data from three cities indicates significant impacts on certain crime types arising from changes in social dynamics due to regulations implemented in response to the COVID-19 pandemic. The results of pair-wise t-tests, appropriately corrected for replication, show that the crime dynamics experienced in 2020 significantly differ from previous years and that the implementation of strict stay at home orders in all three cities initially impacted crime.

Chicago's total crimes during the first three months of the year (including the time period following the stay at home order) declined in 2020 compared to 2017, 2018, and 2019 (see Tables S1-S9). Before COVID protocols were put in place, there were no significant changes in total crimes compared to 2018 and 2019. There were some changes in particular crime types that may have been due to social factors, policing protocols, or other mechanisms. There were also significant changes in total crimes between 2017 and 2020, with all but weapons violations showing declines (Table S9). Once the stay at home order was put in place, there were more stark significant differences between past years and 2020 (see Tables S10, S11, and S12). Total crimes during this time period declined compared to the past three years. There are a number of different crime types contributing to this decline, and few of the contributing crime types are interpersonal. The exceptions are significant declines in assaults and batteries between 2017 and 2019 compared to 2020 (Tables S10 and S12). These results show that the crime dynamics of 2020 are significantly different from those in past years and that the changes would not have been expected based on observations prior to the pandemic outbreak.

We also compared the crime numbers in Chicago between different time periods. Comparing crime types before the stay at home order was put in place to the time after implementation indicates that most of the crime types tested showed significant differences. They include total crimes, assaults, burglaries, criminal sexual assaults, criminal trespasses, interference with public officers, narcotics, other offenses, robberies, and thefts (Table 2, Figure S2). This shows that the immediate time period after stay at home orders were announced do correlate with decreased total crimes, but that the crimes contributing to this decline are related more to property crimes than to interpersonal crimes.

To determine whether this pattern holds in other cities, we also carried out time period comparisons for Baltimore, MD and Baton Rouge, LA (Table 2). Both cities showed similar results. In Baltimore, comparing the time period before the stay at home order was implemented and the two weeks after shows that total crimes, auto thefts, and larceny showed significant differences. For Baton Rouge, total crimes, narcotics, and other crimes showed significant differences when comparing the two weeks after the stay at home order was put in place and the time period before the order was implemented.

In all of our tests across different years and different time periods, we find that the implementation of social distancing and quarantine protocols initially led to significant decreases in crime. Total crimes declined in Chicago after the stay at home order was put in place, but the crime types contributing to this decline are mostly property-based rather than interpersonal. Similar patterns hold for both Baltimore, Maryland and Baton Rouge, Louisiana. Both cities showed declines in crimes after the introduction of stay at home orders. As in Chicago, the crime types contributing to this decline are more often targeting property rather than individuals. It is worth noting that these patterns may have only been present in the initial time period following implementation and may not persist over longer time periods.

The observed patterns could be the result of several different mechanisms. First, there may be differences in policing and reporting under stay at home orders. For interpersonal crimes, victims who are quarantined with their abusers may be less likely to speak up. Social distancing may prevent law enforcement officers from responding to

and reporting certain crime types. This pattern may also arise from individuals spending less time in public spaces and in social interactions. The exact reasons contributing to this change in crime dynamics are difficult to determine, but it is clear that in the immediate time period following implementation of stay at home orders, there was a significant change in crime in Chicago, Baltimore, and Baton Rouge.

This study has a number of limitations. There is differential data availability across the three cities. Chicago has far more crime types publicly accessible for analysis, and there is no consensus on how the data are collected and reported nationally. We have also only analyzed the data for three cities. This pattern therefore may not exist across all regions, especially if adherence to stay at home orders differs between cities. The use of *t*-tests also limits the information we can obtain from these data. Finally, we have only observed the two weeks following the implementation of stay at home orders. The declines in crime may be limited to this time period and not subsist. Recent reports show that violent crime has increased as cities are reopening [1].

These limitations leave open questions for future research. First, there is a need to explore the data presented here more in depth using various statistical tests, expanding the temporal window, or exploring confounding variables in all three cities. Additionally, analysis of patterns of crime data from additional cities is necessary to verify that the observed changes are national in scope. There is also a need to determine some of the mechanisms which have produced these declines and how adherence to stay at home orders impacts the crimes which occur. Overall, stay at home orders produced declines in crime over the initial time period and the crimes contributing to this decline were mainly property-based. The COVID-19 pandemic responses present a forced social experiment impacting many behavioral components and providing opportunities for novel explorations of the connection between behavioral constraints and crime. Given our results, the vigorous public policy debates regarding the impacts of potential interventions on violent crime, particularly gun crime, could benefit from further detailed analysis of imposed regulations arising from the pandemic.

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