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When COVID-19 and guns meet: A rise in shootings

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ABSTRACT

Objective: The present study examines the impact of the COVID-19 stay-at-home order on gun violence in Buffalo, New York: fatal shootings, all non-fatal shootings, non-fatal shootings with injury, and non-fatal shootings without injury. It also estimated its impact on gang and non-gang related shootings.
Methods: Weekly crime data are analyzed at the city level using ARIMA and poisson models. Forecasting is used to verify the validity of both ARIMA and poisson models.
Results: The effect of the pandemic was conditional upon the types of gun violence and impact models of intervention. The pandemic caused a temporary increase in fatal shootings while leading to a long-term increase in all non-fatal shootings, non-fatal shootings with injury, non-fatal shootings without injury, and gang related shootings.
Conclusions: The pandemic has changed the volume of gun violence possibly due to increased strain and/or changed routine activities. This study not only promotes further research but also has policy implications for public health and safety. From a public policy perspective, criminal justice agencies should focus more attention and resources on gun violence resulting from a sense of strain and fear among individuals during the pandemic.

1. Introduction

The outbreak of COVID-19, or more commonly called coronavirus, started in early 2020 in the United States and has influenced every aspect of daily life. Its impact has been expansive and devastating with far reaching implications for individuals and society. As of November 2020, more than 11 million individuals had confirmed cases, and more than 250,000 died of coronavirus infection (Centers for Disease Control and Prevention, 2020). Stay-at-home (SAH) orders were issued across states to prevent the spread of coronavirus, resulting in substantial changes in individuals' daily activities. There has been growing research attention on the impact of the pandemic on crime. The pandemic has changed the volume and distribution of crime as a result of increased strain and/or changed routine activities (Stickle & Felson, 2020). Study outcomes are often conditional upon crime type and differ across locations. Due to the recency of the pandemic and data limitations, the empirical evidence of its impact on crime is scarce, which calls for more research attention.

One area where research can inform our understanding of the impact of COVID-19 on crime is gun violence, which is of a great concern across the United States. There has been notable media attention to recent spikes in gun violence during the pandemic. According to the Federal Bureau of Investigation (2020), there was an unprecedented surge in the number of background checks for gun sales from 2,802,467 in February to 3,740,688 in March, which corresponds to a 33% increase for a single month. The number of background checks in September 2020 already exceeded the total in 2019. A recent increase in gun purchases may result from a sense of insecurity and fear that there will be social unrest and violence, and the government may not protect people (Everytown Research & Policy, 2020a). More gun availability may lead to more intentional and accidental shootings, leading to increased deaths and injuries. Using an annual panel data from 1981 to 2010 across 50 states, Siegel, Ross, and King (2013) found that states with high levels of firearm ownership have higher gun-related homicides than their counterparts.

Using weekly data from Buffalo, NY, the present study examines the impact of the COVID-19 pandemic on gun violence and fills an important gap in our understanding of crime. A few studies examined changes in U.S. homicides and shootings during the pandemic as part of other types of crime (Abrams, 2020; Campedelli, Aziani, & Favarin, 2020). They did not discuss each crime type on a deeper level from the theoretical perspectives. The present study is the first attempt to examine how gun violence changed in response to the pandemic and what types of gun violence experienced greater changes between the pre- and post-

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intervention periods. It discusses gun violence on a deeper level in the contexts of strain and routine activity theories. It also disaggregates gun violence into four categories by death and injury: fatal shootings, all non-fatal shootings, non-fatal shootings with injury, and non-fatal shootings without injury. Further, it estimates the impact of the pandemic on gang and non-gang related shootings. For more exhaustive model specifications, both ARIMA and poisson models are used to estimate whether there was a significant increase in gun violence during the pandemic. Finally, this study extends prior studies on the pandemic and crime by expanding the pre- and post-intervention observations covered for statistical analyses. Before presenting its outcomes, this study provides empirical and theoretical foundations for understanding the pandemic-gun violence association.

2. Literature review

2.1. Prior research

The pandemic is a new social phenomenon; thus, little empirical research has examined the impact of COVID-19 and its resulting SAH order on crime. Some studies examined the effect of the SAH order on crime in large cities in the United States (Abrams, 2020; Ashby, 2020; Mohler et al., 2020). Its effect differed by crime type and across locations. Using a dataset obtained from Los Angeles and Indianapolis, Mohler et al. (2020) found varying effects of the SAH order among different types of crime. They analyzed daily counts of calls for police service from January to April 2020. There was a significant increase in domestic violence and a decline in traffic stops across two cities. The SAH order significantly decreased burglaries and robberies in Los Angeles only. In addition, Abrams (2020) investigated the effect of the SAH order on several crime types using time series data from 2015 to May 2020 across 25 large cities. The SAH order is associated with an increase in non-residential burglary, car theft, robbery, and aggravated assault. However, there was no decrease in murders and shootings. Campedelli et al. (2020), using daily crime data from 2017 to March 2020 in Los Angeles, found evidence of decreases in robbery, shoplifting, theft, and battery. No significant changes were found for vehicle theft, burglary, assault with a deadly weapon, intimate partner assault, and homicide.

Other studies focused on one city for a particular crime type, such as domestic violence and burglary. Piquero et al. (2020) examined the impact of the SAH order on domestic violence in Dallas, Texas. Both OLS and poisson regression models were used to analyze daily data from January to April 2020. There was a significant increase in domestic violence following the announcement of the SAH order. In addition, Felson, Jiang, and Xu (2020) explored the impact of the containment order on burglaries in Detroit, Michigan. They examined changes in the volume and distribution of burglaries during the month of March 2020. The unit of analysis was 879 block groups. The effect of the containment order varied depending on the type of land use. Due to changes in routine activities, burglaries were more likely to occur in the areas with mixed land use, relative to those with residential land use.

There are several studies at the international level. These inquiries also found that the effects of the pandemic and resulting containment measures vary by the type of crime and country. Poblete-Cazenave (2020) and Calderon-Anyosa and Kaufman (2020) found considerable decreases in murders in India and Peru, respectively. However, Balmori de la Miyar, Hoehn-Velasco, and Silverio-Murillo (2020) presented that homicides remained the same during the pandemic in Mexico.

In sum, existing research compared various types of crime across cities before and after the pandemic. It is difficult to offer a simple statement about whether the pandemic exerts a significant effect on crime. The effect of the pandemic varied according to the location of study and across different types of crime. It is still early to draw conclusions about how the pandemic has affected crime. There are several limitations to the current body of research. Given the use of short-term post-intervention observations, prior studies did not capture any long-term impact of the SAH order. Most studies also used short-term pre-intervention observations as a control series that spanned only a few months. There are limits to the ability of prior studies to control for seasonal trends that occur over a one-year period of time. Finally, prior studies have examined the effects of the SAH order in large urban areas. No research was conducted in mid-sized or small metro areas or rural areas.

The above limitations of prior studies call for the present study with relatively long-term pre- and post-intervention series obtained from a mid-sized city. While focusing on gun violence, this study analyzes disaggregated data including fatal vs. non-fatal shootings and gang vs. non-gang related shootings. The use of disaggregated data will extend the existing literature by providing additional insights on the effect of the pandemic on gun violence.

2.2. Theoretical framework

There are several theories to explain how the COVID-19 pandemic and its accompanying SAH order led to an increase in gun violence. The first theoretical foundation comes from strain theory, explaining how crime is related to strain. A disjuncture between socially ascribed goals (e.g., job prestige, wealth, and social status) and legitimate means available to achieve such goals creates strain in individuals, which increases the likelihood of criminal coping (Merton, 1938; Messner & Rosenfeld, 2006). There was an increase in the U.S. unemployment rate from 4.4% in March of 2020 to 14.7% in April immediately following the SAH orders (Falk, Carter, Nicchitta, Nyhof, & Romero, 2020). The effects of the pandemic differed across various groups and industries. The SAH orders took a heavy toll on part-time workers who were employed in leisure and hospitality industries providing in-person services (Falk et al., 2020). Individuals are likely to commit crimes out of strain when they become unemployed and cannot make ends meet for survival through legitimate means during the public health and economic crises.

Gun violence is also linked to general strain theory, which broadened the concept of strain. There are three sources of strain: failure of achieving conventional social goals, removal of positive stimuli, and experience of negative stimuli (Agnew, 2006). The COVID-19 pandemic and its accompanying SAH orders removed positive stimuli by decreasing the availability of employment, leading to lower incomes and increased poverty. Although social distancing is essential to prevent the spread of coronavirus, it has increased social isolation and caused harm to individuals' mental health, such as anxiety, depression, and loneliness. These negative experiences generated strain among individuals, which might exert more pressure on them to engage in gun violence.

Finally, routine activity theory may predict or explain changes in gun violence as a result of the COVID-19 SAH orders. Three elements should exist in time and place for the occurrence of a crime: a motivated offender, a suitable target, and the absence of a capable guardian (Cohen & Felson, 1979). People may experience financial distress and social isolation during the pandemic, and they may turn to increased alcohol consumption to cope with these stressors. Evidence indicates that there were increases in alcohol consumption among adults during the pandemic (Pollard, Tucker, & Green, 2020; The Nielson Company, 2020). Excessive alcohol consumption resulted in anxiety, depression, and high-risk behaviors, such as crime and gun-related incidents (Greenfield, 1998; Pollard et al., 2020).

As previously discussed, many people bought new guns to deal with feelings of uncertainty, insecurity, and fear resulting from the pandemic. This behavior increased the opportunities for potential offenders to engage in gun violence. Siegel et al. (2014) found a positive association between gun ownership and nonstranger gun homicide rates. Specifically, increased gun ownership led to more gun homicides among nonstrangers relative to those among strangers. Laqueur, Kagawa, McCort, Pallin, and Wintemute (2019) also found that high gun sales led to an increase in the number of firearm injuries.

The SAH order could be an effective crime prevention method by limiting contacts between potential offenders and victims. However, given that many people have resisted following social distancing requirements, it is possible that motivated offenders would converge in time and space with potential victims in private and public settings. In the context of high unemployment, alcohol consumption, and gun purchases, people are likely to end up being in fights and other crime-producing situations, increasing the potential for gun violence. Gun homicides often occur among acquaintances in social gatherings (Siegel et al., 2014).

The third component of routine activity theory, the absence of a capable guardian, is also impacted by COVID-19. With being vulnerable to the spread of coronavirus, criminal justice agencies have made adjustments to their daily practices for public health and safety. For example, police officers in Buffalo substantially reduced their DWI arrests 40%, and traffic stops decreased by 45% (personal communication with the Police Deputy Police Commissioner, October 2020). Thus, while street-level officers continued to patrol, and remained present as a capable guardian, some types of self-initiated activity decreased, very likely because of fear of the coronavirus. There was also evidence of declines in police stops and arrests across 26 large cities after the SAH orders were implemented to decrease the spread of coronavirus (Abrams, 2020; Mohler et al., 2020). In the absence of capable guardians due to a substantial reduction in proactive police behavior, a combination of increased strain associated with unemployment, social drinking, and gun purchases might have contributed to increases in gun violence.

2.3. Present study

Based on these empirical and theoretical frameworks, the following hypothesis will be tested: *The COVID-19 pandemic and its corresponding*

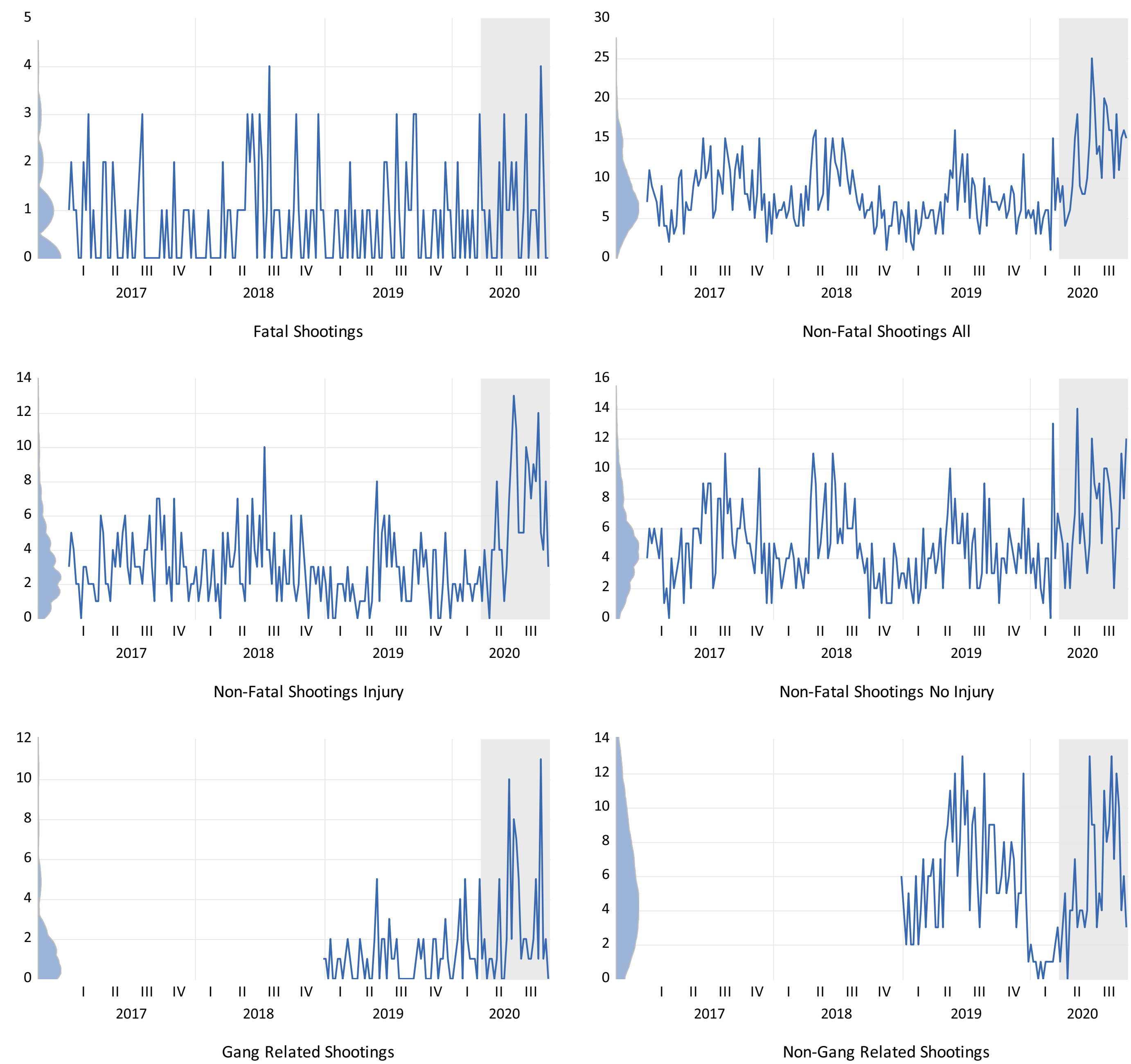

Fig. 1. Shootings in Buffalo.

SAH order increased gun violence in Buffalo, controlling for seasonality and other historical trends. There are four types of gun violence: fatal shootings, all non-fatal shootings, non-fatal shootings with injury, and non-fatal shootings without injury. This study also tests whether the pandemic has affected gang and non-gang related shootings. The city of Buffalo, known as a rust belt city, is a mid-sized metro area with a population of more than 250,000 people. It has higher rates of unemployment, poverty, and violent crime relative to the national average (U. S. Bureau of Labor Statistics, 2020; U.S. Census Bureau, 2019; Federal Bureau of Investigation, 2019). The pandemic might have put residents under more strain and pressure, resulting in increased criminal behavior. Therefore, Buffalo is an ideal place to examine the association between the pandemic and gun violence.

Fig. 1 shows a visual illustration of temporal changes in the numbers of shootings in Buffalo. The shaded area in Fig. 1 represents the post-intervention period from 3/23/2020 to 10/5/2020. All types of non-fatal, gang related, and non-gang related shootings demonstrated apparent upward trends with repeating spikes and drops following the SAH intervention. On the other hand, there was a spike in fatal shootings during the first intervention week, and the series immediately fell to its prior level in the next week. Afterward, fluctuations in the post-intervention time series for fatal shootings were of approximately the same magnitude as those in the pre-intervention period. It is important to statistically test whether such increases in all the time series resulted from the pandemic, while controlling for covariates and secular trends.

3. Method

3.1. Data

The data were provided by the Erie Crime Analysis Center (ECAC) that is a centralized repository for crime information in Erie County, New York. There are four dependent variables: fatal shootings, all non-fatal shootings, non-fatal shootings with injury, and non-fatal shootings without injury. For interrupted time series analysis, this study includes the period from January 2017 to the first week of October 2020. The time frame for the study includes a total 197 observations. In addition, this study conducted analyses for gang and non-gang related shootings. However, the data for gang and non-gang related shootings are only available back to January 2019 with a total 93 observations. The unit of analysis is weekly incidence of shootings at the city level, presenting the number of incidents per week in Buffalo. In prior studies, crime counts, instead of crime rates, were used as an outcome measure given that population data were not available on a weekly or monthly basis (e.g., Kim, Phillips, & Wheeler, 2019; Loftin & McDowall, 1984; Loftin, McDowall, Wiersema, & Cottey, 1991; O'Carroll et al., 1991; Phillips, Kim, & Sobol, 2013; Piquero et al., 2020).

The independent variable is the COVID-19 pandemic. In New York state, Governor Cuomo put in place a SAH order on March 20. The effective date was Sunday, March 22. All non-essential businesses were closed, and workers and residents were ordered to stay home, which affected public interactions to a great extent. The specification of the intervention point is an important methodological issue. It is often difficult to discern when the pandemic started to exert an effect on crime. This study used the SAH order as the beginning point of the intervention under the assumption that it might take some time until COVID-19 gained awareness among citizens and influenced their daily routines. A dummy variable was created to measure the pandemic intervention. 168 observations prior to the week of March 23rd were coded as zero, and 29 observations from March 23 and afterwards were coded as one. It should be noted that the SAH order is not the independent variable, just the beginning point of the pandemic when governmental restrictions caused substantial disruption to normal social behavior and interactions. Although the SAH order ended on June 13 and its requirements and restrictions were relaxed at the time of this writing, the pandemic still caused substantial socio-economic disruptions to residents. There were continuing increases in confirmed cases, high unemployment rates, and many restrictions on daily activities. Hence, this study uses the pandemic as the independent variable, not the SAH order.

The volume of gun violence could be impacted by BLM protests and resulting depolicing actions. A dummy variable was constructed to control for the potential effects of local protests on gun violence. Six observations, including the weeks of 5/25 to 6/29, were coded as one, and otherwise coded as zero. Across the country, the Black Lives Matter (BLM) movement resulted in large-scale protests after the death of George Floyd in Minneapolis on May 25. In Buffalo, protests started on May 30, and an incident on June 4 resulted in a citizen being seriously injured. Two Buffalo police officers were charged with a crime, causing 57 police officers to resign from their roles on an emergency response team (Miller, Culver, Robinson, Hauck, & Taddeo, 2020). It is possible that police officers across the city pulled back on patrols and arrests for crime and disorder. This "depolicing" action (see Nix, Wolfe, & Campbell, 2018; Phillips, 2020 for a fuller discussion of depolicing) may send a message to potential offenders that a community lacks formal social control, leading to an increase in gun violence in the absence of capable guardians.

Seasonality is an important consideration when analyzing time series data. Seasonality was captured in a dummy variable (Q2-3). It took the value of one if shooting incidents occurred in the second and third quarters of the year and zero otherwise. Buffalo has experienced a long winter season with heavy snows and low temperatures, leading to significant decreases in crimes and other social activities in the fourth and first quarters (Kim et al., 2019). Prior studies found a positive association between temperature change and crime (Baron & Ransberger, 1978; Cohn & Rotton, 2000; Field, 1992; Rotton & Cohn, 2000). In addition, more than three pre-intervention years were included in the models to rule out any historical effects. Given that both pre- and post-intervention series are influenced by a similar set of factors, they should be similar in level if there were no intervention.

3.2. Statistical analyses

There are three key components in this study: ARIMA intervention models, poisson/negative binomial regression models, and forecast evaluations for model comparison. First, ARIMA intervention modeling assesses the impact of the COVID-19 pandemic on various types of shootings. As an effective quasi-experimental design, it has been used for hypothesis testing (Cook & Campbell, 1979). It also allows modeling various impact patterns of intervention while effectively dealing with the problem of non-stationarity. Second, passion/negative binomial regression is used because the dependent variables are count data and/or not normally distributed. As seen in Fig. 1, the Kernel Density plots indicate that all time series are positively skewed. Only non-gang related shootings passed the Jarque-Bera test (JB statistic = 4.37, p = .11), indicating that non-gang related shootings are not significantly skewed. Especially, there is a concern over the non-normality for fatal shootings. There are 96 zeros (49%) out of a total sample of 197 observations, and the distribution of fatal shootings is skewed with a long tail in the positive direction. Third, forecasting has been an important part of time-series analysis for model checking. To verify the validity of both ARIMA and poisson regression models, this study examined how observed values differ from the predicted values estimated from the models.

4. Results

4.1. Descriptive statistics and t-tests

This study compared pre- and post-intervention means to examine whether any difference can be attributable to the intervention and large enough to be statistically significant. As shown in Table 1, the COVID-19

Table 1
Pre- and Post-Intervention Means of the Time Series.

Variable	Pre-Int. Mean (SD)	Post-Int. Mean (SD)	Change in mean	*t*-Test t (p)
Dependent variables				
Fatal shootings	0.73 (0.91)	1.07 (1.13)	+0.34	−1.77[a]
Non-fatal shootings all	7.41 (3.43)	12.79 (5.14)	+5.38	−7.19**
Non-fatal shootings injury	2.83 (1.87)	5.83 (3.43)	+3	−6.88**
Non-fatal shootings no injury	4.58 (2.46)	6.97 (3.10)	+2.39	−4.62**
Gang related shootings	1.02 (1.19)	2.72 (3.02)	+1.70	−3.92**
Non-gang related shootings	5.42 (3.38)	5.89 (3.55)	+0.47	−0.62

Notes. For fatal and non-fatal shootings, pre-intervention period: 1/2/2017–3/16/2020 (168 weeks) and post-intervention period: 3/23/2020–10/5/2020 (29 weeks).
For gang- and nongang-related shootings, pre-intervention period: 12/31/2018–3/16/2020 (64 weeks) and post-intervention period: 3/23/2020–10/5/2020 (29 weeks).
** Significant at $\alpha = 0.01$.
[a] Significant at $\alpha = 0.10$.

pandemic led to significant increases in non-fatal shooting incidents at the 0.01 level. All non-fatal shootings, with a mean of 7.41 before the order went into effect, increased to a mean of 12.79 thereafter. Specifically, non-fatal shootings with and without injury significantly increased from a mean of 2.83 to 5.83 and 4.58 to 6.97, respectively. Shootings in which death occurred rose from a mean of 0.73 to 1.07, which was insignificant at a conventional significance level ($p < .01$ or 0.05). Finally, the pandemic significantly increased gang related shootings from a mean of 1.02 to 2.72, while there was no significant difference between the pre- and post-pandemic means for non-gang related shootings.

4.2. *Autoregressive integrated moving average (ARIMA) intervention models*

Three analytic steps are needed for ARIMA models: identification, estimation, and diagnosis (McDowall, McCleary, Meidinger, & Hay, 1980). The first step involved the identification of ARIMA models. Several unit roots tests were performed for the presence of non-stationarity, including the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwlatkowski-Phillips-Schmidt-Shin (KPSS) tests. Once a stationary variable was obtained, the autocorrelation function (ACF), partial autocorrelation function (PACF), and Box-Ljung Q statistics were used to test for the presence of dependence in a given time series.

The second step involved the estimation of intervention models. This study used two impact patterns to model the function of the pandemic: an abrupt-temporary model for fatal shootings and a gradual-permanent model for all non-fatal shootings, non-fatal shootings with injury, and non-fatal shootings without injury, gang related shootings, and non-gang related shootings. As seen in Fig. 1, the abrupt-temporary impact model is more appropriate for fatal shootings. The time series experienced an immediate spike in the first week of the intervention and reverted to its pre-intervention level without any lingering effect. On the other hand, the gradual-permanent impact model is more plausible in consideration of gradual and permanent increases in three types of non-fatal shootings, gang related shootings, and non-gang related shootings. Many weeks were needed to reach its full impact on the volume of shootings. The last step was to carry out diagnostic checks for the intervention models. This study examined the ACF and PACF of the residuals obtained from the fitted models. In addition, it formally tested for serial correlation, heteroscedasticity, and normal distribution.

4.2.1. *Model Identification*

Using the pre-intervention observations, this study performed various unit root-tests to examine whether a time series is non-stationary. The ADF and PP tests examined the null hypothesis of a unit root, and the KPSS test examined the null hypothesis of stationarity. Table 2 presents that all dependent variables do not have a unit root and are thus stationary. In addition, the Canova-Hansen test examined whether a time series has a seasonal unit root. The results show no significant seasonal variation in all dependent variables at a conventional significance level ($p < .01$ or 0.05). Finally, the patterns of serial correlation in the ACF and PACF were examined to define the white noise ARIMA models: ARIMA (0,0,0) for fatal shootings, ARIMA (1, 0, 6) for all non-fatal shootings, ARIMA (1,0,1) for non-fatal shootings with injury, ARIMA (1, 0, 1) for non-fatal shootings without injury, ARIMA (0,0,2) for gang related shootings, and ARIMA (1,0,0) for non-gang related shootings.

4.2.2. *Fatal shootings*

The results of ARIMA models are reported in Table 3. The intervention coefficient (ω) indicates the changes in the number of fatal shootings following the SAH order. The intervention is significant in the abrupt-temporary model. Specifically, there was an increase of 2.44 fatal shootings during the first week of the intervention. However, its effect disappeared immediately. In addition, there were 0.30 more fatal shootings per week in the second and third quarters of the year, compared to the first and fourth quarters. Finally, the residual diagnostics present no significant autocorrelation and heteroscedasticity in the residuals. According to the Jarque-Bera test, there is evidence that the residuals of the models are not normally distributed.

4.2.3. *Non-fatal shootings*

As seen in Table 3, the effect of the intervention is significant for all non-fatal shootings and non-fatal shooting without injury in the gradual-permanent models ($p < .05$). The effect of the pandemic on non-fatal shootings with injury is significant only at the 0.1 level. For example, the intervention coefficient (ω) for all non-fatal shootings is 0.60, indicating that non-fatal shootings increased by 0.60 incidents per week. Given the gradual parameter (δ) is significant at the 0.01 level, it is important to estimate the long-term effect of the intervention (McDowall et al., 1980). The long-term effect on all non-fatal shootings was 4, or 0.60/(1–0.85). Specifically, the level of the series increased by 0.60 in the first post-intervention week. After the intervention, the level of the series continues to increase with each passing week. The equation can be expressed as: $y_t = \delta y_{t-1} + \omega(1)$. Thus, the second post intervention observation is 1.07, the third is 1.24, the fourth is 1.35, and so on. The

Table 2
Results for Unit Root Tests of the Pre-Intervention Time Series.

Variables	Aug. DF Level	PP Level	KPSS Level	CH Level
Fatal Shootings	−11.81**	−11.85**	0.08	0.24
Non-Fatal Shootings All	−4.25**	−10.84**	0.25	0.75
Non-Fatal Shootings Injury	−11.35**	−12.04**	0.37	.99[a]
Non-Fatal Shootings No Injury	−6.03**	−11.48**	0.17	0.34
Gang Related Shootings	−7.51**	−7.51**	0.18	0.41
Non-Gang Related Shootings	−4.25**	−4.37**	0.35[a]	0.89[a]

Notes. For fatal and nonfatal shootings, 1/2/2017–3/16/2020 (168 Weeks); For gang- and nongang-related shootings, 12/31/2018–3/16/2020 (64 Weeks).
Aug. DF-GLS = Augmented Dickey Fuller. PP = Phillips-Perron. KPSS = Kwlatkowski-Phillips-Schmidt-Shin. CH = Canova-Hansen. Figures for unit root tests represent a t-statistic in a model with constant.
** Significant at $\alpha = 0.01$.
[a] Significant at $\alpha = 0.10$.

Table 3
ARIMA and Poisson Models for Fatal and Non-Fatal Shootings.

Variable/ Model	Fatal		Nonfatal All		Nonfatal Injury		Nonfatal No Injury	
	ARIMA (0, 0, 0)	POISSON	ARIMA (1, 0, 6)	QMLNBR (V = 0.026448)	ARIMA (1, 0, 1)	POISSON	ARIMA (1, 0, 1)	POISSON
Intercept (c)	0.56 (0.11)**	−0.56 (0.15)**	0.79 (0.26)**	1.62(0.07)**	0.18 (0.06)**	0.69 (0.08)**	0.86 (0.37)*	1.22(0.07)**
COVID-19 (ω)	2.44 (0.94)*	1.66(0.60)**	0.60 (0.23)*	0.28 (0.08)**	0.15 (0.10)[a]	0.37 (0.12)**	0.49 (0.21)*	0.27 (0.09)**
Q 2–3	0.30 (0.14)*	0.40 (0.17)*	0.68 (0.20)**	0.32 (0.06)**	0.23 (0.07)**	0.35 (09)**	0.59 (0.23)*	0.35 (0.07)**
BLM	0.41 (0.39)	0.36 (0.37)	0.83 (0.40)*	−0.02 (0.15)	0.95 (21)**	0.14 (0.19)	−0.24 (0.33)	−0.19 (0.18)
δy_{t-1}	0.04 (0.07)	0.05 (0.08)	0.85 (0.04)**	0.03 (0.01)**	0.90 (0.02)**	0.06 (0.02)**	0.75 (0.10)**	0.02 (0.01)a
AR(1)	–	–	–[b]	–	–[b]	–	–[b]	–
MA(1)	–	–	−0.75 (0.06)**	–	−0.88 (0.04)**	–	−0.67 (0.11)**	–
MA(6)	–	–	–[b]	–	–	–	–	–
Adj. R-squared	0.05	0.05	0.42	0.38	0.36	0.32	0.22	0.20
SIC	2.80	2.47	5.31	5.22	4.31	4.15	4.72	4.61
Ljung-Box Q	NA	NA	NA	NA	NA	NA	NA	NA
Correlogram	NA	NA	NA	NA	NA	NA	NA	NA
ARCH								
F-statistic	0.02	–	0.97	–	0.05	–	0.07	–
Obs*R^2	0.02	–	0.98	–	0.05	–	0.07	–
Jarque-Bera	48.54**	50.01**	10.87**	18.76**	6.85*	13.43**	29.87**	60.63**

Notes. Pre-intervention period: 1/2/2017–3/16/2020 (168 weeks). Post-intervention period: 3/23/2020–10/5/2020 (29 weeks).
NA = No Autocorrelation.
The abrupt-temporary model was used for fatal shootings, while the gradual-permanent model was used for non-fatal shootings.
** Significant at $\alpha = 0.01$.
* Significant at $\alpha = 0.05$.
[a] Significant at $\alpha = 0.10$.
[b] AR or MA terms were removed from the models due to their lack of significance.

number of all non-fatal shootings continued to increase, but the effect of the intervention became smaller and smaller over time at a slow pace. Hence, the intervention resulted in an eventual increase of 4 non-fatal shootings per week. Similarly, non-fatal shootings without injury rose by 0.49 per week. The long-term effects were estimated to be an increase of 1.96 non-fatal shootings without injury.

The seasonal term is statistically significant in all models. There were increases in the number of non-fatal shootings in the second and third quarters of the year when people would be expected to engage in more social interactions. The BML variable was significant in all non-fatal shootings and non-fatal shootings with injury. Finally, all models are free from autocorrelation and heteroscedasticity in the residuals. However, the residuals are not normally distributed in all models.

4.2.4. *Gang related shootings*

The pandemic had a significant impact on gang related shootings. There was an increase of 1.49 gang related shootings per week during the pandemic. Given that the gradual parameter is almost zero and not significant, the increase in gang related shootings was instantaneous or abrupt. Both seasonal and BLM variables were not significantly associated with gang related shootings. Finally, the residual diagnostics indicate no significant autocorrelation and heteroscedasticity in the residuals. According to the Jarque-Bera test, there is evidence of non-normality in the residuals.

4.2.5. *Non-gang related shootings*

The pandemic was not significant in explaining an increase in non-gang related shootings. Seasonality was positively associated with non-gang related shootings. The Jarque-Bera test presents that the residuals of the model are normally distributed. However, the null hypothesis of no ARCH effects was rejected at the 0.5 level in the ARCH LM test with a one period lagged squared residual and a constant. For comparison purposes, this study performed additional tests for heteroskedasticity. Both the Brusch-Pagan-Godfrey and Harvey tests indicated no presence of heteroskedasticity in the residuals. Furthermore, this study estimated an ARCH (1) model to adjust for potential ARCH effects. However, the coefficient of e^2(−1) in the variance equation of the ARCH model was negative and insignificant (b = −0.13, $p = .40$), which did not meet the necessary and sufficient condition for an ARCH model. In addition, there were no notable difference between the ARCH (unreported) and ARIMA (reported) models in the coefficient estimates of all variables in terms of their significance, direction, and magnitude.

4.3. *Poisson/negative binomial regression models*

Given that the dependent variables were count data and/or not normally distributed, this study conducted poisson regression for more exhaustive model specifications. Poisson models have been used to model count data where the time series is positively skewed with many zero counts. They have several benefits over the ARIMA models. They do not require a normal distribution of the errors for count data. They also improve accuracy of predictions by restricting their predictions to non-negative numbers.

The present study conducted a regression-based test for the poisson assumption of variance-mean equality (Cameron & Trivedi, 1990; Cameron & Trivedi, 2013). Specifically, it ran a poisson regression of a dependent variable, estimated its predicted values, and ran an auxiliary linear regression of $e^2 - y \ on \ \hat{y}^2$. The coefficients of $\hat{y}^2$ in the auxiliary regression model of all non-fatal shootings (0.026448) and gang related shootings (0.780229) were significant at the 0.05 or 0.01 level, indicating overdispersion in the residuals. Using the estimate of $\hat{y}^2$ as a fixed variance parameter, quasi-maximum likelihood negative binomial regression (QMLNBR) was used to correct for overdispersion (Gourieroux, Monfort, & Trognon, 1984). For fatal shootings, non-fatal shootings with injury, non-fatal shootings without injury, and non-gang related shootings, poisson regression was used since the models did not violate the assumption of equidispersion at the 0.05 level. The results are shown in Tables 3 and 4.

Coefficients are interpreted as the difference in the natural logs of expected counts for shootings as a function of the intervention. To facilitate interpretation, the coefficient of the intervention was exponentiated and expressed as an incidence rate ratio (Long, 1997). While holding other variables constant in the gradual-permanent model, the expected count of all non-fatal shootings increased by a factor of 1.32 during the pandemic. In percentage terms, the percentage change in the expected count of all non-fatal shootings is 32, or 100 × (1.32–1). Similarly, in the post-intervention period, there was a significant increase in the expected count of non-fatal shootings with injury, non-fatal shootings without injury, and gang related shootings by 45%, 31%, and

Table 4
ARIMA and Poisson Models for Gang and Non-Gang Related Shootings.

Variable/ Model	Gang		Non-Gang	
	ARIMA (0, 0, 2)	QMLNBR (0.780229)	ARIMA (1, 0, 0)	POISSON
Intercept (c)	1.04 (0.34)**	0.04 (22)	2.43 (60)**	1.08 (0.10)**
COVID-19 (ω)	1.49 (0.55)**	0.92 (0.33)**	−0.93 (0.76)	−0.15 (0.11)
Q 2–3	−0.06 (0.46)	−0.08 (0.31)	2.61 (0.76)**	0.51 (0.12)**
BLM	1.20 (0.91)	0.40 (0.48)	0.30 (1.32)	0.06 (0.19)
δy_{t-11}	−0.00 (11)	0.01 (0.06)	0.34 (0.10)**	0.06 (0.01)**
AR(1)	–	–	–[a]	–
MA(2)	–[a]	–	–	–
Adj. R-squared	0.12	0.12	0.31	0.27
SIC	4.38	3.50	5.13	5.13
Ljung-Box Q	NA	NA	NA	NA
Correlogram	NA	NA	NA	NA
ARCH				
F-statistic	0.24	–	4.95*	–
Obs*R^2	0.25	–	4.95*	–
Jarque-Bera	112.36**	50.95	3.66	6.68*

Notes. Pre-intervention period: 12/31/2018–3/16/2020 (64 weeks); Post-intervention period: 3/23/2020–10/5/2020 (29 weeks).
NA = No Autocorrelation.
** Significant at $\alpha = 0.01$.
* Significant at $\alpha = 0.05$.
[a] AR or MA terms were removed from the models due to their lack of significance.

151%, respectively. For fatal shootings, the impact of the intervention was represented by a pulse function, as consistent with those in the ARIMA models. In the first week of the intervention, the expected count of fatal shootings rose by a factor of 5.26, provided other variables remained the same. However, the time series reverted to its pre-intervention level due to the temporary effect of the pandemic on fatal shootings.

4.4. Forecast evaluation for model comparison

To examine the accuracy of the models, the present study compared the observed data with the data predicted by the fitted models. Although the goal of forecasting is to predict unknown future values, it is implausible to evaluate whether the fitted model accurately predicts out-of-sample due to data unavailability of future incidents. One must wait to estimate the accuracy of forecasts.

Alternatively, the present study performed an ex-post out of sample forecast evaluation. The data were divided into two segments: *history* (1/2/2017–7/27/2020, 187 observations or 12/31/2018, 83 observations) and *artificial future* (8/3/2020 10/5/2020, 10 observations). This study estimated a model over the *history* period and made one-step ahead predictions over the *artificial future* period. The static forecasting method used the actual value of a lagged dependent variable to make each subsequent forecast. The accuracy of forecasts was estimated by considering how well the model predicts the artificial future observations.

Fig. 2 plots observed and predicted values for the ARIMA and poisson models that were identified as the best fit to each dependent variable: the abrupt-temporary model for fatal shootings and the gradual-permanent models for all types of non-fatal shootings and gang and non-gang related shootings. Overall, the forecasts did not capture the highs and lows of actual volatility in the time series; thus, the predicted values were less volatile than the observed values. The forecasts underestimated the number of shooting incidents when there was a sharp spike in the series and overestimated when the series plummeted at high speed.

Two diagnostic measures examined the difference between the observed series and those predicted by a fitted model: RMSE (Root Mean Squared Error) and Thiel's U_1 (Thiel Inequality Coefficient). Lower values of both measures indicate a better fit to the data. RMSE is the

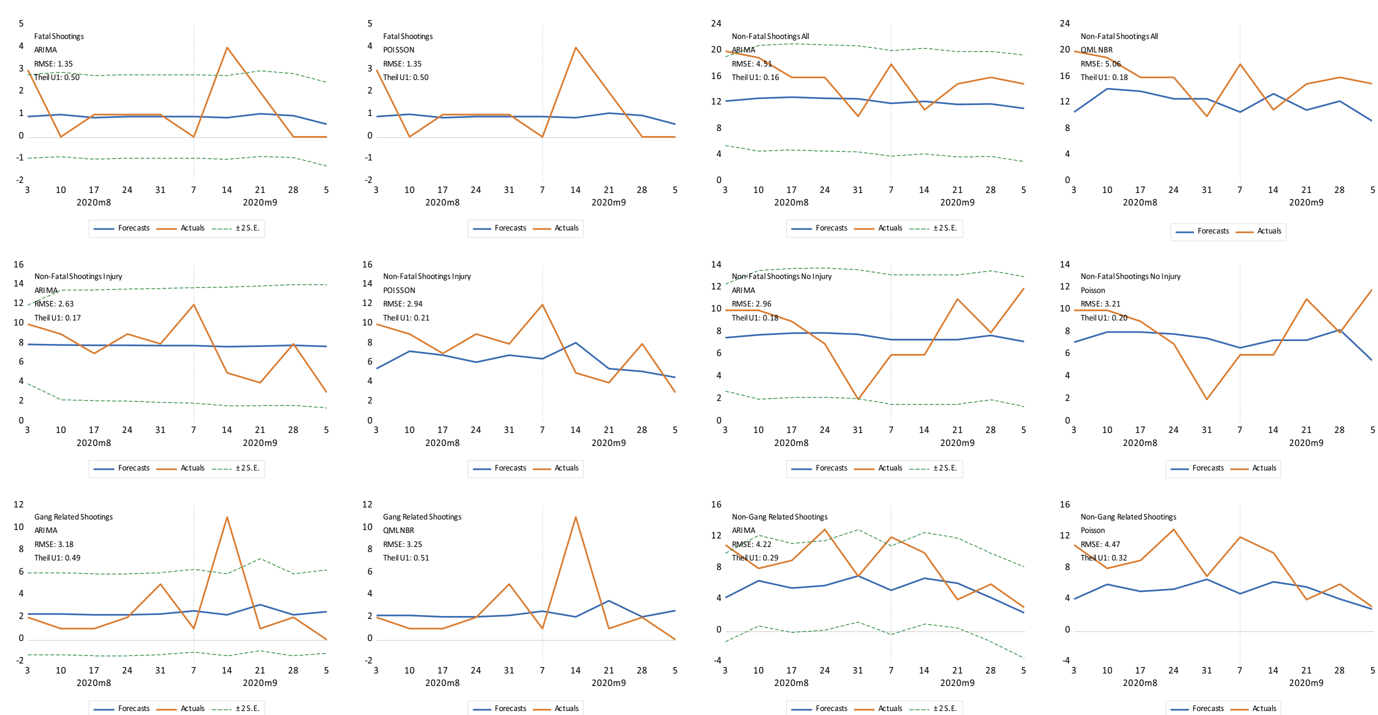

Fig. 2. Forecast Evaluation for ARIMA and Poisson Models. Notes. For fatal and non-fatal shootings, Estimation Sample: 1/2/2017–7/27/2020 (187 observations). Forecast Sample: 8/3/2020 10/5/2020 (10 observations). For gang- and non-gang related shootings, Estimation Sample: 12/31/2018–7/27/2020 (83 observations). Forecast Sample: 8/3/2020 10/5/2020 (10 observations).

standard deviation of residuals. For example, the RMSE for all non-fatal shootings in the ARIMA model is 4.51, indicating that the predicted data are 4.51 shootings, on average, away from the observed data. Given that RMSE values are conditional upon the scale of the time series, they can be compared only for the same time series. In addition, Theil's U_1 estimated the degree to which the predicted values differ from the observed values (Cook, 2019; Leuthold, 1975). It ranges from zero to one, with a value of zero indicating a perfect fit and one indicating that the forecasts are no better than those offered by a naïve guess. This coefficient is scale-invariant.

Forecasting was used to compare the relative validity of the ARIMA and poisson models. Overall, both RMSE and Thiel's U_1 measures for all types of non-fatal shootings, gang related shootings, and non-gang related shootings indicate lower values for the ARIMA models, as opposed to the poisson models. Thus, the ARIMA models have a greater predictive ability than the poisson models. For fatal shootings, both RMSE and Thiel's U_1 measures indicate the same value between the ARIMA and poisson models; there is no difference in predicting fatal shootings.

5. Discussion

The research examined whether the COVID-19 pandemic and its resulting SAH order influenced gun violence in Buffalo. The effect of the pandemic differed across types of gun violence. Both ARIMA and poisson models showed similarities in the effect of the pandemic on gun violence. There were gradual and permanent increases in the number of both non-fatal and gang related shootings during the pandemic. In addition, the pandemic led to an abrupt and temporary increase in the level of fatal shootings. However, the finding for fatal shootings should be interpreted with caution. It is not clear whether the spike in the first intervention week was attributable to the pandemic alone or part of historical trends in which fatal shootings fluctuated over the sample period.

The results of the current study should be compared to other studies in this area. Abrams (2020) found no significant increase in homicides and shootings during the pandemic across 25 large cities in the United States. In addition, no significant change was detected for homicides and assaults with a deadly weapon in Los Angeles (Campedelli et al., 2020). At the international level, the effects of the pandemic on homicides differed by country. Murders decreased in India (Poblete-Cazenave, 2020) and Peru (Calderon-Anyosa & Kaufman, 2020) during the pandemic but remained stable in Mexico (Balmori de la Miyar et al., 2020). Given that prior studies did not distinguish between homicides with guns and other weapons and between fatal and non-fatal shootings, it is difficult to directly compare them with the results of the present study. Aggregate crime data cannot capture a complex picture of varying impact patterns of the pandemic across different types of homicides and gun violence, which calls for further research with disaggregated data.

In this study, the COVID 19 pandemic had more significant effects on non-fatal and gang related shootings, relative to fatal and non-gang related shootings. Given the temporary or insignificant impact of the pandemic on fatal and non-gang related shootings, it is plausible that recent increases in both non-fatal and gang-related shootings are related to each other. The increase in non-fatal shootings might have resulted in part from the increase in gang related shootings. The bivariate correlation between all non-fatal shootings and gang related shootings is moderate and positive, $r(93) = 0.46$, $p = .00$.

Strain theory may support the current findings. For example, the pandemic led to an unprecedented increase in the unemployment rate, especially for poor individuals in the inner city. It became more difficult for them to earn enough money for survival. Individuals who are placed in circumstances of structural unemployment and poverty were likely to experience strain, and such feeling may lead them to engage in gun violence during the pandemic.

In addition, routine activity theory may explain significant increases in both non-fatal and gang related shootings. During the pandemic, there was an increase in pop-up parties for drinking in Buffalo (Becker & Besecker, 2020). Social distancing requirements and restrictions on the number of people allowed in bars and nightclubs led young people to organize social gatherings in parking lots, vacant lots, or even on side streets. When alcohol consumption is part of these parties, shootings would seem more likely to break out among crowds of young adults intentionally, spontaneously, or even accidently.

These pop-up parties might have increased the probability that motivated offenders would converge in time and space with potential victims in the absence of police officers due to the fear of coronavirus, increasing the likelihood of gun violence particularly in the context of high unemployment, alcohol consumption, and gun purchases. Pop-up parties were presented via social media, and in some instances 200–300 people would attend (Becker & Besecker, 2020). Currently, the Buffalo Police Department do not collect information on situational characteristics of gun violence. It is thus implausible to estimate how much of the increase in gun violence was attributable to shootings at pop-up parties. There should be collaborative efforts between researchers and practitioners to examine the effects of the pandemic on gun violence.

During the pandemic, there were a series of Black Lives Matter (BLM) protests and unrest in Buffalo following the death of George Floyd in May, possibly leading to depolicing actions among officers in response to negative publicity and criminal charges. The atmosphere of de-policing could be perceived for motivated offenders as lacking formal control and promote their gun violence. In this study, however, the association between the BLM variable and gun violence was sensitive to the type of gun violence and models. The BLM variable was insignificant in most models. It turned out to be significant in both all non-fatal shootings and non-fatal shootings with injury in the ARIMA models only. Additional research is required to investigate whether BLM protests had different effects across locations. It is also important to explore officer perceptions of depolicing on whether and how BLM protests disengage them from daily work for crime prevention due to the fear of criminal scrutiny. Such research attention will contribute to a greater understanding of the causal mechanism between the pandemic and crime mediated by changes in the presence of police officers.

6. Implications for research

It is important to discuss the study's limitations and corresponding implications for future research. First, interrupted time series analysis is a strong quasi-experimental design for testing the impact of intervention, but it is susceptible to internal validity threats such as history (Cook & Campbell, 1979). In this study, the inability to include a comparison area to reduce this problem, as the pandemic is global and no reasonable comparison can be identified, required a prolonged pre-intervention period (more than three years) to control for secular trends. Second, given the use of a single city and the varying effects of the pandemic across different socio-economic contexts, it is difficult to generalize current findings to other places. When the data allow, future research should examine changes in gun violence by location. It is also important to use small geographic entities (census tracks, block groups, and census blocks) as units of analysis to examine varying effects of the pandemic across locations.

The unavailability of structural covariates on a weekly basis precluded this study from using them as controls. Given that the unit of analysis for this study is weekly data at the city level, it was difficult to get weekly information on structural covariates. Future research should examine whether the increase in gun violence was directly attributable to increased unemployment, alcohol consumption, and gun purchases (Sutherland, McKenney, & Elkbuli, 2020). For example, job availability was significantly decreased in some service sectors, such as leisure and hospitality (Falk et al., 2020). This worsened the economic plight of under-educated and employed individuals, which ultimately will increase poverty and economic inequality. Since the unemployment-crime association was often found to be positive in the literature, other scholars should examine the extent to which unemployment had an impact on crime during the pandemic. In addition, the Coronavirus Aid, Relief, and Economic Security (CARES) Act is an economic stimulus bill to reduce the devastating effects of the public health and economic crises resulting from the pandemic. It is important to examine whether the CARES Act buffered the effect of unemployment on gun violence. This type of research will guide public policy and practice for the public health and safety of citizens.

Research concerning the impact of the pandemic on gun violence is becoming very important, especially as gun purchases and gun violence has received renewed attention during the pandemic. This study fills a gap in the literature by examining recent spikes in gun violence in a mid-sized city. Given the evolving nature of the pandemic, it is imperative to continue estimating its impact on gun violence and other crimes over time across places using a range of research designs. Research endeavors should be as enduring as the prolonged impact of the pandemic.

7. Implications for policy

The present study uncovers an important policy question of how to reduce gun violence during the pandemic. Recent gun and ammunition purchases were motivated by a sense of uncertainty and insecurity among ordinary citizens about the volatile state of the nation. The pandemic resulted in a change in the practice of individuals' gun storage. Due to the evolving and uncertain nature of the pandemic, some gun owners used less secure methods of gun storage (Kraviz-Wirtz, Aubel, Schleimer, Pallin, & Wintemute, 2020). They kept guns at the ready, loaded up and/or unlocked, in the home. Loosening gun storage practices might increase the likelihood of homicides, suicides, and other unintentional shootings (Anglemyer, Horvath, & Rutherford, 2014). Those who buy for self-defense are likely to keep loaded and unlocked guns within easy reach, which ironically might increase risk for gun incidents (Anglemyer et al., 2014; Kravitz-Wirtz et al., 2020). Citizens should be encouraged to adhere to social distancing measures and safely store any firearms. Consistent with routine activity theory, changes in individuals' routines in gun storage can reduce spontaneous acts of gun violence in social gatherings.

There are several ways to reduce gun-related deaths and injuries during the pandemic. One important method is community-based public safety programs, such as street outreach programs, group violence intervention, hospital-based violence intervention programs, and cognitive behavioral therapy (Everytown Research & Policy, 2020b). All of them intended to address gun violence by reducing strain among individuals and situational criminal opportunities through innovative urban and architectural designs. They have been implemented to reduce gun violence in economically disadvantaged neighborhoods in inner cities. Providing mental health and medical services is another way to decrease the negative effects of the pandemic on gun related deaths and injuries (Stone et al., 2017). It is important to identify and support individuals at risk of shooting or being shot and teach coping skills to deal with feelings of strain and fear about the uncertainty of the pandemic. Finally, the pandemic has increased unemployment, poverty, and economic inequality, which can contribute to gun violence. It is important to provide economic support policies for employment, housing, and basic expenses. For example, the CARES Act was enacted to provide financial assistance for individuals and families.

High rates of gun violence in the United States continue to spark national debate about gun control and is a critical issue for researchers and policymakers. Given the right of individuals to own firearms, the development of effective gun control policies can be the first step to address gun violence. It is beyond the scope of the present study to discuss how to control the possession and use of guns, which is still debatable in the United States. Additional policy and research attention are needed to identify the most promising gun control and public health policies.

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