COVID-19 and Gun Violence: Keeping Unknown Shocks and Volatility in Perspective

Dae-Young Kim

Abstract
The current study estimates the varying effects of the pandemic on gun violence by social distancing type, fatality, and location. Interrupted time series analyses are used to examine weekly crime data from 2016 to 2020 in New York City. Box-Cox power transformation and GARCH techniques are used to address the problems of non-normality and heteroscedasticity in the models. There were significant increases in fatal and non-fatal shootings during the relaxation of social distancing. The impact of the BLM protests and depolicing is significant for non-fatal shootings. The pandemic led to greater increases in gun violence in The Bronx, Brooklyn, Manhattan, and Queens, as opposed to Staten Island. In addition, there is some evidence of increases in the volatility of gun violence during the pandemic. High volatility implies crime rates are in severe flux, which then leads to greater uncertainty and fear for public safety. This paper surfaces useful information for guiding policy and practice.

Keywords
COVID-19, ARCH/GARCH, gun violence, shootings, social distancing

Introduction
As the coronavirus has spread widely across many countries, the World Health Organization (WHO) declared the outbreak of COVID-19 a global pandemic in March 2020 (WHO, 2020). The pandemic is not an exception to the United States. Since the first cases of the coronavirus were confirmed in January 2020, the number of reported cases has exponentially increased across the country. Various types of containment measures were issued to prevent the spread of the coronavirus, including closures of schools, daycares, non-essential workplaces, and borders (Kaimann & Tanneberg, 2021). The implementation of containment measures differed across places in onset, length, and intensity (Mervosh et al., 2020; Ortiz & Hauck, 2020).

There have been unintended consequences of the pandemic on gun violence. As a result of the pandemic and social distancing, individuals are forced to be physically isolated, deal with...
unexpected unemployment and pay cuts, suffer from serious medical complications, and/or experience a feeling of strain (American Psychological Association, 2020; Falk et al., 2020; United Nations, 2020), all of which might have led to increases in gun violence. The empirical evidence in the United States is mixed and inconclusive. Some studies found significant increases in gun violence (Kim, 2022; Kim & Phillips, 2021; Rosenfeld & Lopez, 2020), while no significant changes were detected in other studies (Abrams, 2020; Campedelli et al., 2020). Overall, the pandemic-gun violence association is significant and greater in studies with relatively long-term post-pandemic data. The pandemic might take several months to make an impact on gun violence. Given the newness of the pandemic and a lack of sufficient evidence, further research should be performed for more accurate conclusions correlating the pandemic and gun violence.

Using crime data from 2016 to 2020 in New York City, the current study explores the varying effects of the pandemic on gun violence by social distancing type, fatality, and location. Specifically, this study analyzes whether gun violence decreased or increased under the SAHO and/or during the relaxation of social distancing. In addition, this study will fill a gap in the literature by disaggregating gun violence by fatality and borough, estimating how the impact of the pandemic differs depending on whether a fatality occurs and where a shooting occurs. Furthermore, it explores whether high unemployment rates during the pandemic are associated with increased gun violence. Finally, the Box-Cox transformation and GARCH methods are used to deal with the problems of heteroscedasticity and non-normality resulting from omitted variable bias, which will improve the reliability of the study outcomes. GARCH modeling also allows for examining changes in the variance of gun violence and thereby explaining its volatility during the pandemic, which will provide important implications for both policy makers and practitioners. In the following section, an overview of theoretical and empirical frameworks will be offered for the study of gun violence during the pandemic.

**Literature Review**

**Theoretical Background**

Strain theory can explain increases in gun violence as a result of the pandemic and its corresponding containment measures. It discusses why certain individuals or groups have higher crime rates than others. Drawing on the work of Durkheim on suicide, Merton (1938) applied the concept of anomie to explain high crimes in the United States. Crime is seen as a consequence of anomie or strain resulting from a discrepancy between a cultural emphasis on material success and legitimate means to attain such a goal (Merton, 1938; Messner & Rosenfeld, 1997, 2006). When people are caught in structural unemployment, poverty, and inequality, they are more likely to rely on illegal but more convenient means (i.e., crimes) out of monetary strain and/or to achieve socially ascribed economic goals. Another theoretical explanation of strain and crime is general strain theory, which expanded the sources of strain beyond the failure to attain material success. Agnew (2006) identified three situations of crime-producing strain: failure to attain commonly held goals (monetary success and social status), removal of positive stimuli (the loss of intimate relationships and the death of family members), and presentation of negative stimuli (isolation, insults, physical abuse, and criminal victimization).

To put the theories into context, it is important to discuss the underlying reasons for the pandemic-gun violence association. People experienced psychological distress and strain through a range of negative events, such as limited access to employment, quality health care, healthy diets, and social interaction (United Nations, 2020). For example, the practice of social distancing meant to slow the spread of the coronavirus by limiting face-to-face contact among people. However, it had adverse impacts on individuals’ mental health and wellbeing, including stress, frustration, loneliness, anxiety, and depression (Panchal et al., 2021). In addition, the pandemic and containment orders forced many businesses and factories to
shut down, resulting in a sharp rise in the unemployment rate from 4.4% in March 2020 to 14.7% in April 2020 (Falk et al., 2020) in the United States and from 4.2% to 15.5% in NYC (U.S. Bureau of Labor Statistics, 2020). There is strong theoretical and empirical evidence to expect a relationship between unemployment and crime. After reviewing 63 previous aggregate studies, Chiricos (1987, p. 187) concluded that there were "consistently positive and frequently significant" unemployment-crime relationships. The relationships are significant and greater, especially when unemployment is structural (Carlson & Michalowski, 1997) and/or not enough social welfare policies are offered to reduce the harshest effects of economic downturns (Batton & Jensen, 2002).

During the pandemic, many individuals purchased new or additional guns for several reasons: lawlessness, prisoner release, the government going too far, government collapse, and closures of gun stores (Kraviz-Wirtz et al., 2021, p. 6). An analysis of annual data from 1981 to 2010 revealed that gun availability is positively associated with gun-related homicides across 50 U.S. states (Siegel et al., 2013). As seen in Figure 1, there were unprecedented increases in firearm background checks for gun sales during the pandemic era. Specifically, the number of firearm background checks had increased in NYS (US) from 355,374 (28,369,750) in 2019 to 507,940 (39,695,315) in 2020, corresponding to a 42.93 (39.92) percent increase year over year (FBI, 2021). As a proxy for measuring the number of firearm purchases, firearm background checks are susceptible to over- and under-estimating problems (Lang, 2016). For example, given that firearm background checks just indicate people’s intention to buy firearms, they might not necessarily lead to firearm purchases. Firearm background checks do not capture transactions across states, especially from states with strict gun laws to those with weak gun laws.

Substance use is also a coping behavior in response to strain during the pandemic and has significantly increased among adults (Panchal et al., 2021; Pollard et al., 2020). For example, there has been a substantial increase in online alcohol purchases amid the stay-at-home order (SAHO) and other containment restrictions, as on-premise establishments, such as bars and restaurants, shut down (The Nielsen Company, 2020). In the meta-analysis of 30 experimental studies, Bushman and Cooper (1990) concluded that "alcohol does indeed cause aggression" (p. 341). Alcohol use interferes with people’s intellectual functioning, self-awareness, and assessment of risks, ultimately increasing their risk-taking and violent behavior.

Figure 1. Firearm background checks, month/year. Source: Federal Bureau of Investigation National Instant Criminal Background Check System.
During the pandemic, there were intense BLM protests against police brutality and racial bias in late May and mid-June, which might influence the volume of gun shootings. Although most protesters were peaceful in NYC, many people were charged with rioting and various types of crime (Celona & Barone, 2020; NYC Department of Investigation, 2020). Protesters can also be victims of crime during the BLM protests. In addition, the BLM movement and its resulting protests might have caused a depolicing phenomenon, also called the Minneapolice effect (Cassell, 2020). While being overwhelmed by public criticism and civil disobedience, police officers might retreat from law enforcement duties (Nix et al., 2018; Phillips, 2020). There were significant decreases in police homicides across the neighborhoods when they experienced large and frequent BLM protests (Campbell, 2021). Gun violence might increase as more resources were assigned to deal with the BLM protests.

Table 1. Descriptive Statistics and T-Tests, Total N = 261.

| Variable | Min. | Max. | Mean | Pre-Int. Mean (SD) | Post-Int. Mean (SD) | Change in Mean | t (p) |
|----------|------|------|------|-------------------|-------------------|----------------|-------|
| By Fatality |      |      |      |                   |                   |                |       |
| Fatal    | 0    | 18   | 4.38 | 3.75 (2.63)       | 7.76 (4.61)       | + 4.01         | - 7.78** |
| Non-Fatal| 3    | 78   | 18.71| 15.75 (6.68)      | 34.63 (19.05)     | + 18.88        | - 11.47**|
| Total    | 4    | 96   | 23.09| 19.50 (7.81)      | 42.39 (22.37)     | + 22.89        | - 11.86**|
| By Location |     |      |      |                   |                   |                |       |
| Bronx    | 0    | 28   | 6.50 | 5.63 (3.77)       | 11.17 (6.83)      | + 5.54         | - 7.43** |
| Brooklyn | 0    | 48   | 9.21 | 7.53 (4.77)       | 18.24 (11.39)     | + 10.71        | - 10.06**|
| Manhattan| 0    | 24   | 3.11 | 2.66 (2.09)       | 5.49 (4.38)       | + 2.83         | - 6.43** |
| Queens   | 0    | 15   | 3.62 | 3.12 (2.44)       | 6.34 (3.37)       | + 3.22         | - 7.28** |
| Staten Island | 0 | 7 | .74 | .66 (97) | 1.17 (1.64) | + 0.51 | - 2.71** |

Notes: Pre-intervention period: 1/3/2016–3/15/2020 (220 weeks); Post-intervention period: 3/22/2020-12/27/2020 (41 weeks).

** Significant at α = .01.
followed by few stops, questions, and frisks in hot spot areas as part of proactive policing (Cassell, 2020).

Routine activity theory is another theoretical approach that explains the association between individuals’ criminal behavior and routine activities during the pandemic. For a crime to happen, there should be a convergence of a motivated perpetrator and a suitable target of victimization in the absence of a capable guardian for the victim and/or property (Cohen & Felson, 1979). As discussed above, the pandemic and containment orders might have resulted in an increase in the number of potential offenders motivated by various sources of strain. Individuals might have engaged in gun violence out of strain due to job loss, financial difficulty, and psychological distress about the volatile state of the pandemic.

The effect of the pandemic may differ by location, particularly residential versus public places (Kim & McCarty, 2021). Amidst an increase in confirmed cases of the coronavirus and its containment measures, people were ordered to stay at their place of residence. Thus, gun violence is more likely to occur in residential areas where motivated offenders and suitable targets spend more time under the SAHO. On the other hand, people were prohibited from associating with others outdoors, which might reduce the confluence of potential offenders and victims in time and place and corresponding gun violence in public areas. Given that many people refused to comply with social distancing guidelines (Fitzsimons, 2020; Stanley-Becker & Janes, 2020), motivated offenders could still engage in gun violence outdoors.

**Empirical Background**

The focus of the literature review is on aggregate studies of gun violence and homicide during the pandemic (Abrams, 2020; Campedelli et al., 2020; Kim, 2022; Kim & Phillips, 2021; Rosenfeld & Lopez, 2020). Most studies were conducted in the United States, and the empirical evidence is mixed. For example, using the difference-in-difference design, an examination of weekly crime data from January 2015 to May 2020 across 25 cities revealed no significant changes in homicides and shootings following the containment measures (Abrams, 2020). In addition, a Bayesian structural time-series analysis of daily crime data in Los Angeles from January 2017 to March 2020 found no evidence of significant changes in homicides and assaults with a deadly weapon (Campedelli et al., 2020).

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**Table 2. Unit Root and Normality Tests of the Pre-Intervention Time Series, Total $N=220$.**

| Variable          | Aug. DF | PP    | KPSS | HEGY  | CH    | J-B   |
|-------------------|---------|-------|------|-------|-------|-------|
| **By Fatality**   |         |       |      |       |       |       |
| Fatal             | -12.50** | -12.71** | .08  | 20.05* | .63   | 56.87** |
| Non-Fatal         | -6.31** | -11.64** | .23  | 46.65** | .59   | 20.05** |
| Total             | -6.33** | -11.69** | .20  | 44.78** | .59   | 35.32*  |
| **By Location**   |         |       |      |       |       |       |
| Bronx             | -12.28** | -12.43** | .15  | 24.74* | .71   | 617.44** |
| Brooklyn          | -7.70** | -13.28** | .27  | 20.46* | .78   | 85.04** |
| Manhattan         | -13.41** | -13.51** | .21  | 23.59** | .71   | 165.31** |
| Queens            | -14.20** | -14.20** | .15  | 55.51*** | .51   | 105.73** |
| Staten Island     | -15.05** | -15.07** | .63* | 21.77*** | .72   | 1038.37** |

Notes: Aug. DF = Augmented Dickey Fuller-GLS; PP = Phillips-Perron; KPSS = Kwiatkowski-Phillips-Schmidt-Shin; CH = Canova-Hansen; HEGY = Likelihood-Ratio HEGY; J-B = Jarque-Bera. Aug. DF, PP, and HEGY test whether the series is non-stationary, while KPSS and CH test whether the series is stationary. Figures for unit root tests represent a t-statistic in a model with constant.

* Significant at $\alpha = .05$; ** Significant at $\alpha = .01$. 

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On the other hands, Kim and Phillips (2021) study estimated the impact of the pandemic on gun violence in Buffalo, NY. Both ARIMA and poisson models were used to examine weekly time series variation in shootings from January 2017 to October 2020. During the pandemic, there were significant increases in non-fatal and gang related shootings. A significant increase in fatal shootings was noted, but the effect of the pandemic was abrupt and temporary. In addition, using monthly census tract data in NYC from January 2017 to March 2021, Kim (2022) examined the effect of the pandemic on gun violence, without differentiating between fatal and non-fatal shootings, and its interaction with time constant neighborhood characteristics. Gun violence significantly increased during the pandemic and was significantly associated with poverty, economic inequality, minority populations, residential mobility, and the total population. No significant interaction effects between the pandemic and neighborhood characteristics were found in the study.

Using crime data from 2017 to October 2020, Rosenfeld and Lopez (2020) found substantial increases in homicide and gun assault across 28 cities, while controlling for seasonal patterns. Using the January 2019 to March 2020 data from the Washington, DC Metropolitan Region, Chodos et al. (2021) found that firearm-related injury significantly increased during the pandemic, especially in urban areas. Sutherland et al. (2021) also detected increases in gun violence from 2018 to April 2020 in Baltimore, Chicago, Los Angeles, and NYC. However, the statistical analyses for Chodos et al.’s (2021) and Sutherland et al.’s (2021) studies were descriptive in nature, which failed to adjust for seasonality and other covariates. Thus, the results should be interpreted with caution.

There are several studies outside of the United States. Using data from January to May of 2019 and 2020 in Mexico City, Mexico, Balmori de la Miyar et al. (2020) found no significant effects of the lockdown on homicide. On the other hand, significant decreases in homicides during the lockdowns period were found in India (Poblete-Cazenave, 2020) and Peru (Calderon-Anyosa & Kaufman, 2020). Their effects were abrupt in onset and short-lived in duration.

Figure 3. Simulated ARCH process.
Prior research has compared crime trends across cities and countries before and after the containment measures were put into place. Given that prior studies focused on explaining increases in the means of gun violence (e.g., Balmori de la Miyar et al., 2020; Calderon-Anyosa & Kaufman, 2020; Chodos et al., 2021; Kim & Phillips, 2021; Rosenfeld & Lopez, 2020; Sutherland et al., 2021), the research will fill a gap in the literature by examining changes in both the mean and variance of gun violence using GARCH modeling. Specifically, it examines the extent to which gun violence increased during the pandemic and whether such changes occurred under the SAHO and/

![Figure 4. The optimal Box-Cox transformation of the time series. Notes: The red line indicates the optimal lambda value that minimizes the variance of each time series.](image)

**Table 3.** Box-Cox Power Transformation Models for Shootings by Fatality, Total N = 261.

| Variable/Model | Fatal $\lambda=.30$ | Non-Fatal $\lambda=.30$ | Total $\lambda=.26$ |
|---------------|----------------------|-------------------------|---------------------|
| Intercept     | .79 (.21)**          | 1.46 (.27)**            | 2.08 (.24)**        |
| SAHO          | .43 (.28)            | .36 (.29)               | .40 (.26)           |
| SAHO Relaxed  | 1.06 (.20)**         | 1.47 (.26)**            | 1.56 (.20)**        |
| BLM           | .25 (.52)            | 1.27 (.53)**            | 1.08 (.47)*         |
| Temperature   | .02 (.00)**          | .03 (.00)**             | .03 (.00)**         |
| $\delta Y_{t-1}$ | .16 (.06)**       | .12 (.06)*              | .15 (.06)*          |
| $\delta Y_{t-2}$ | -.08 (.06)         | .12 (.06)*              | -                   |
| Adj. R-squared | .25                  | .55                     | .56                 |
| SIC           | 2.67                 | 2.72                    | 2.46                |
| Serial Cor LM $\text{Obs}^R^2$ | 3.48                  | .67                     | 4.13                |
| Jarque-Bera*  | .34                  | 2.69                    | 1.63                |
| ARCH $\text{Obs}^R^2$ | .35                  | .18                     | .34                 |

Notes: Pre-intervention period: 1/3/2016–3/15/2020 (220 weeks); Post-intervention period: 3/22/2020-12/27/2020 (41 weeks).

†Significant at $\alpha = .10$; * Significant at $\alpha = .05$; ** Significant at $\alpha = .01$. 

Prior research has compared crime trends across cities and countries before and after the containment measures were put into place. Given that prior studies focused on explaining increases in the means of gun violence (e.g., Balmori de la Miyar et al., 2020; Calderon-Anyosa & Kaufman, 2020; Chodos et al., 2021; Kim & Phillips, 2021; Rosenfeld & Lopez, 2020; Sutherland et al., 2021), the research will fill a gap in the literature by examining changes in both the mean and variance of gun violence using GARCH modeling. Specifically, it examines the extent to which gun violence increased during the pandemic and whether such changes occurred under the SAHO and/
or during the relaxation of social distancing. It also analyzes the volatility of gun violence during the pandemic. The volatility of crime trends is as much a problem as rising crime itself. High volatility indicates wide and unpredictable fluctuations of crime levels over time, increasing people’s fear of crime and uncertainty about public safety. Both the Box-Cox transformation and GARCH methods are used to address the problems of heteroscedasticity and/or non-normality in the models. These methodological methods have not been widely used in the literature. Most studies did not report any statistics on whether their models had any non-normality and/or heteroscedasticity problems.

Another area where future research leads to a deeper understanding of the pandemic and gun violence is to examine what underlying factors were associated with increased gun violence. Among many possible factors, unemployment rates are a focus of the research. Prior to the pandemic, unemployment rates in NYC were low and remained fairly steady at about 4.38 on average (see Figure 2). However, they began skyrocketing in April 2020 and reached the highest peak in May at 20.20 with an average rate of 14.79 during the pandemic. Such a coincidence that both unemployment rates and gun violence present increasing trends during the pandemic era calls for the present study.

This study explores whether the pandemic exerted differing effects on gun violence by location and fatality. First, given that most studies were conducted only at the city or national level (Abrams, 2020; Balmori de la Miyar et al., 2020; Calderon-Anyosa & Kaufman, 2020; Campedelli et al., 2020; Kim & Phillips, 2021; Rosenfeld & Lopez, 2020; Sutherland et al., 2021), future research is warranted to examine whether the impact of the pandemic varies across small geographic units within a city. The pandemic and its socio-economic fallout increased strain disproportionately among economically disadvantaged individuals (Centers for Disease Control and Prevention, 2020; Panchal et al., 2021). Gun violence would be more prevalent in poor and/or densely populated urban boroughs during the pandemic, compared to their suburban counterparts that are more affluent and/or less densely populated. Historically, the problems of gun violence have been centered on young Black males who live in urban ghettos (Courtwright, 1996; Kaiser Family Foundation, 2021).

According to the U.S. Census Bureau (2021), The Bronx (24.4%), Brooklyn (17.8%), and Manhattan (16.3%) have higher poverty rates, as opposed to Staten Island (10.6%) and Queens (10.3%). In addition, Manhattan is the most densely populated borough in the city (69,467.5 per square mile), followed by Brooklyn (35,369.1), The Bronx (32,903.6), Queens (20,553.6), and Staten Island (8,030.3). The Bronx is the borough with the largest minority population (55.3%), subsequently followed by Brooklyn (50.2%), Queens (42.2%), Manhattan (35.4%), and Staten Island

| Variable/Model | Intercept | SAHO | SAHO Relaxed | BLM | Temperature | Adj. R-squared | Serial Cor LM | Jarque-Bera | ARCH |
|----------------|-----------|------|--------------|-----|-------------|---------------|--------------|------------|-------|
| Bronx $\lambda=22$ | 1.07 (.18)** | .18 (.25) | .96 (.16)** | 1.19 (.47)* | .02 (.00)** | .28 | 2.43 | 1.02 | .00 |
| Brooklyn $\lambda=10$ | 1.05 (.13)** | .25 (.19) | 1.09 (.12)** | .65 (.35) | .02 (.00)** | .44 | 1.85 | 1.02 | .48 |
| Manhattan $\lambda=18$ | .70 (.17)** | .233 (.44) | .81 (.15)** | .30 (.44) | .01 (.00)** | .16 | 2.31 | 2.25 | .91 |
| Queens $\lambda=34$ | .78 (.21)** | .42 (.24) | 1.16 (.19)** | .51 (.55) | .02 (.00)** | .20 | 2.75 | 2.69 | 1.61 |
| Staten $\lambda=-1.07$ | .15 (.06)* | .03 (.09) | .10 (.06)† | -.06 (.17) | .00 (.00) | .01 | .40 | .93 | .43 |

Notes: Pre-intervention period: 1/3/2016–3/15/2020 (220 weeks); Post-intervention period: 3/22/2020-12/27/2020 (41 weeks).

†Significant at $\alpha = .10$; * Significant at $\alpha = .05$; ** Significant at $\alpha = .01$. 

Table 4. Box-Cox Power Transformation Models for Shootings by Location, Total N = 261.
Violent crimes are more frequent in urban areas where heterogeneous populations live with high rates of poverty and population density, than in suburban and rural areas (Duhart, 2000; Gibbs, 1979; Ladbrook, 1988). Urban violent victims are more likely than suburban and rural counterparts to be victimized by firearms (Duhart, 2000). During the pandemic, individuals are likely to commit gun violence in densely populated urban boroughs of color where they are caught in situations of structural unemployment and poverty.

Given that most studies have focused on overall gun violence (Balmori de la Miyar et al., 2020; Calderon-Anyosa & Kaufman, 2020; Kim, 2022; Poblete-Cazenave, 2020; Sutherland et al., 2021), this study analyzes disaggregated data (fatal vs. non-fatal shootings). Fatal shootings have been a focus of research and policy attention since they gain more public attention. In contrast, there is a lack of data and research on non-fatal shootings, even if they are more common than fatal shootings and constitute a large share of gun violence (Cook, 1985; Huebner & Hipple, 2018). The use of disaggregated data by fatality may provide important insights for policy development.

There are two theoretical approaches to understanding why certain victims die or survive: criminal intent and the power of firearms (Braga & Cook, 2018). Both perspectives must be seen as complementary, not contradictory, theoretical explanations for the fatality of gun violence. The first explanation is traced to criminal intent. The offender's motive and determination to kill play a critical role in the probability that a victim dies. Second, there is a direct relationship between the type of weapon and the fatality of gun violence, independent of the offender’s intent. The probability of firearm death is closely related to the power and dangerousness of the offender’s firearm as measured by the diameter of a bullet (Braga & Cook, 2018; Zimring, 1972). Large-caliber firearms are more deadly, ultimately increasing the probability of death in gun assaults.

There is some overlap between fatal and non-fatal shootings when it comes to the demographic characteristics (race/ethnicity, age, and gender) of the victims and the circumstances involved in shootings (Braga & Cook, 2018; Hipple & Magee, 2017). The victims of gun violence are often

| Table 5. GARCH Models for Shootings, Total N = 261. |
|---------------------------------------------|
| **Variable/Model** | **Non-Fatal GARCH (1,1)** | **Total GARCH (1,1)** | **Brooklyn GARCH (1,1)** |
| **Mean Eq.** | | | |
| Intercept | 2.71 (1.29)* | 4.68 (1.20)** | -0.08 (0.85) |
| SAHO | 1.14 (3.10) | 4.48 (4.85) | 0.69 (1.21) |
| SAHO Relaxed | 12.89 (2.23)** | 17.50 (1.83)** | 8.22 (1.17)** |
| BLM | 20.13 (11.14)† † | 20.64 (13.68) | 7.98 (4.05)* |
| Temperature | 0.19 (0.03)** | 0.25 (0.03)** | 0.13 (0.02)** |
| δYt−1 | 0.15 (0.07)* | - | - |
| **Variance Eq.** | | | |
| Intercept | 5.63 (3.27)† † | 6.47 (3.54)† | 3.83 (1.28)** |
| e(-1)^2 | 0.22 (0.10)** | 0.27 (0.10)** | 0.28 (0.11)* |
| h(-1) | 0.66 (1.10)** | 0.65 (1.00)** | 0.57 (0.12)** |
| Adj. R-squared | 0.57 | 0.52 | 0.45 |
| SIC | 6.72 | 7.02 | 6.03 |
| Ljung-Box Q36 | 33.83 | 37.12 | 36.78 |
| Jarque-Bera | 5.01* | 8.26** | 35.02** |
| ARCH Obs*R^2 | 0.04 | 0.09 | 0.03 |

Notes: Pre-intervention period: 1/3/2016–3/15/2020 (220 weeks); Post-intervention period: 3/22/2020–12/27/2020 (41 weeks).
† Significant at α = .10; * Significant at α = .05; ** Significant at α = .01.
* The quasi-maximum likelihood covariances were computed to adjust for the problem of non-normality in the residuals (Bollerslev & Wooldridge, 1992).
young minority males with criminal records in poor urban areas (Braga & Cook, 2018). In addition, gangs and drugs have played important roles in the occurrences of gun violence. On the other hand, fatal and non-fatal shootings differ with respect to where they occur. Fatal shootings are more likely to take place indoors, as opposed to non-fatal shootings mostly happening outdoors (Braga & Cook, 2018). Clearance rates for non-fatal shootings were much lower across many cities, especially when they were associated with gangs and drugs, compared to those for fatal shootings (Cook et al., 2019). Non-fatal shooting victims often do not report incidents to police. Instead, they seek retaliation against the perpetrators, leading to a cycle of gun crime and endangering public safety, especially in neighborhoods of color (Hipple et al., 2019; Huebner & Hipple, 2018). In addition, more police resources are geared to investigating fatal shootings, leading to more witnesses and evidence and ultimately higher clearance rates for fatal shootings, as opposed to non-fatal shootings (Barao et al., 2021). Given the above differences between fatal

Figure 5. Forecasting the mean and variance of Gun violence.
and non-fatal shootings, the present study examines whether the pandemic had varying effects on gun violence by fatality.

The Current Study

Based on the above theoretical and empirical frameworks, there are several research questions in this study. First, it examines whether the pandemic led to significant increases in both the mean and/or variance of gun violence and whether such increases occurred under the SAH order and/or during the relaxation of social distancing. Second, it explores which of fatal and nonfatal shootings is more amenable to the impact of the pandemic. Third, it examines whether the pandemic led to more gun violence in poor and/or urban boroughs, as opposed to their affluent and/or suburban counterparts. Fourth, it examines whether high unemployment rates during the pandemic were associated with increased gun violence.

Method

Data

Dependent variables. The dependent variable is gun violence. The data were obtained from the NYC Open Data portal (https://opendata.cityofnewyork.us/). The data include any incident in which a firearm is discharged that is made known to the NYPD, as defined by the NYC Open Data Team Help Desk. Suicides or attempted suicides that involve the use of a firearm are not included in the data. Individual cases were merged into counts on a weekly basis from January 2016 to December 2020. There is a total of 261 observations in the study, providing ample intelligence to estimate the effect of the pandemic on gun violence.

This study examined varying changes in gun violence by fatality and location. First, gun violence is categorized into three groups by fatality: fatal, non-fatal, and the total combined. Second, gun

| Variable/Model       | Fatal $\lambda=0.34$ | Non-Fatal $\lambda=0.30$ | Total $\lambda=0.26$ |
|----------------------|----------------------|--------------------------|----------------------|
| Intercept            | .44 (.21)*           | 1.39 (.20)**             | 1.87 (.18)**         |
| SAHO                 | -.81 (.34)*          | -1.78 (.32)**            | -1.57 (.28)**        |
| SAHO Relaxed a       | -                    | -                        | -                    |
| Unemployment         | .12 (.02)**          | .20 (.02)**              | .19 (.01)**          |
| BLM                  | -.29 (.54)           | .66 (.52)                | .39 (.45)            |
| Temperature          | .01 (.00)**          | .03 (.00)**              | .03 (.00)**          |
| $\delta Y_{t-1}$     | .10 (.06)†           | -                        | -                    |
| Adj. R-squared       | .27                  | .57                      | .59                  |
| SIC                  | 2.74                 | 2.64                     | 2.36                 |
| Serial Cor LM $\text{Obs^*R^2}$ | 3.29                 | 2.14                     | 1.34                 |
| Jarque-Bera$^2$      | .17                  | 6.57*                    | 7.39*                |
| ARCH Obs$^2$R$^2$    | .15                  | .03                      | .00                  |

Notes: Pre-intervention period: 1/3/2016–3/15/2020 (220 weeks); Post-intervention period: 3/22/2020–12/27/2020 (41 weeks).

†Significant at $\alpha = .10$; * Significant at $\alpha = .05$; ** Significant at $\alpha = .01$.

a The SAHO Relaxed variable was removed from the models due to its multicollinearity problem with the unemployment variable.
violence is counted by NYC’s five boroughs: The Bronx, Brooklyn, Manhattan, Queens, and Staten Island. Thus, the unit of analysis is the number of fatal and/or non-fatal shootings per week at the city or borough level.

Figure 2 illustrates the changes in the levels of gun violence by fatality and location. The shaded area indicates the period of the SAHO. Fatal, non-fatal, and the total combined shootings indicate substantial increases at the city level, beginning in May and going through August. Similarly, there were visible increases in shootings across five boroughs during the pandemic. As seen in Table 1, the t-tests confirm that there were significant increases from the pre- to post-SAHO mean regardless of fatality and location.

Unit root tests are used to check for non-stationarity. The ADF and PP tests examine the null hypothesis that a time series is non-stationary, complemented by the KPSS test with the null hypothesis of stationarity. As seen in Table 2, all time series are stationary with no unit root at a conventional significance level ($p < .05$ or .01). It is noted that there is conflicting evidence about the stationarity of shootings in Staten Island. The ADF and PP tests show no unit root at the .01 level, whereas the KPSS test indicates that the series is not stationary at the .05 level. Given the preponderance of evidence of stationarity over non-stationarity, the time series for Staten Island is analyzed in levels rather than in differences. In addition, the Canova-Hansen and Likelihood-Ratio HEGY tests indicate no seasonal unit root for all the time series. In addition, the Jarque-Bera tests report non-normality in all time series at the .05 or .01 significance level. Finally, all time series exhibit unusually large volatility during the pandemic, which may cause heteroscedasticity in the residuals of fitted models. Implications of nonnormality and heteroscedasticity in the series will be discussed in more detail in the section of Statistical Analysis.

**Independent variables.** There are two pandemic-related variables: the SAHO and the relaxation of social distancing (relaxed SAHO). In New York State, the Governor issued a SAHO on March 20. All individuals were mandated to stay in their homes and only allowed to do outdoor activities for essential needs, businesses, and government functions. This order was ended June 26. The SAHO is defined as a dummy variable indicating the presence of the intervention from the weeks of March 22 to June 21 (coded as one) and the absence of the intervention (coded as zero). In addition, the relaxation of social distancing is captured in a dummy variable. It takes the value of one for the weeks of June 28 and afterwards, and zero for all pre-intervention observations.

In addition, unemployment rates are measured using the percentage of the civilian labor force over 16 years of age that is unemployed in NYC. The data were obtained from the U.S. Bureau of Labor Statistics. Given that unemployment data are available at the city level and on a monthly basis, they are used only for city-level analyses of fatal, non-fatal, and the total combined shootings. Unemployment rates are time invariant within each month.

**Control variables.** Two control variables are included in the study: Black Lives Matter (BLM) protests and temperature. First, BLM protests in NYC were initially reported on May 26, and there was a wave of intense civil disturbance in June, composed of demonstrations, riots, and crimes. Although most protesters associated with the BLM movement were peaceful, some protesters became hostile and got involved in various types of crime, such as shootings, looting, and vandalism (NYC Department of Investigation, 2020). Protesters might be also involved as victims of gun violence. In addition, police officers could be disengaged from active policing in crime ridden neighborhoods as a result of hostile public criticism and scrutiny after the death of Floyd. Police resources are spread thin and diverted from crime ridden areas to make mass arrests associated with curfew violations and various crime charges in the wake of the BLM protests (NYC Department of Investigation, 2020). The effect of the BLM protests is measured by a dummy variable. The
weeks of May 24 through June 21, when serious civil unrest occurred in NYC (NYC Department of Investigation, 2020), are coded as one, and otherwise coded as zero.

Second, a continuous variable is created to control for seasonal trends in the time series. The temperature variable represents a degree of warmness or coldness on a Fahrenheit scale. The literature found that temperature is positively related to violent crime (Baron & Ransberger, 1978; Field, 1992; McDowall et al., 2012; McDowall & Curtis, 2015; Rotton & Cohn, 2000). It is thus imperative to take into account seasonality for model specification. Finally, this study uses the long-term pre-intervention time series as a control series spanning over four years. This will improve the research’s causal inference. Also, the sufficient post-intervention observations allow estimating the long-term effects of the intervention on gun violence.

**Statistical Analysis**

This study uses interrupted time series analyses to examine the effect of the pandemic on gun violence, while adjusting for covariates and historical trends. Diagnostic tests assess model adequacy in terms of serial correlation, non-normality, and heteroscedasticity. Autoregressive Distributed Lag (ADL) models are used if the residuals are serially correlated. In addition, GARCH and Box-Cox transformation methods are used to reduce the problems of heteroscedasticity and non-normality in the residuals. If the residuals have the property of serial correlation, heteroscedasticity, and non-normality, the significance tests and corresponding confidence intervals can be invalidated (Lewis-Beck, 1980). It is thus imperative to keep serial correlation, non-normality, and heteroscedasticity in perspective for empirical estimation.

This research devotes more attention to statistical analysis as its focus is on the application of GARCH and Box-Cox power transformation methods to examine volatile trends in gun violence. As yet, both methods have not received full attention for the study of the pandemic and gun violence. A visual inspection of Figure 2 suggests substantial increases in gun violence during the pandemic due to large but unknown shocks to all time series. The series are positively skewed and have heavier tails than the normal distribution. There are also volatility clusters in the series; large changes in the series are often followed by large ones, and small fluctuations are accompanied by small ones.

Large outliers and high volatility in the series can generate heteroscedasticity and non-normality in the residuals of fitted models. Consequently, the standard errors and corresponding confidence intervals tend to be smaller, leading to a mistaken rejection of the null hypothesis (Lewis-Beck, 1980). Given that the problems of heteroscedasticity and non-normality often result from omitted variables, it is important to identify as many covariates as possible. However, the unavailability of data at smaller geographic and temporal units often precludes this approach. For example, alcohol and gun sales are not included in this study, due to a lack of weekly or monthly time series data at the city and borough level. It is thus imperative to statistically address omitted variable biases and corresponding non-normality and/or heteroscedasticity problems in the models using the Cox-Box transformation and GARCH techniques.

As seen in Figure 3, a series of simulated data are constructed to explain how large shocks generate heteroscedasticity in the error structure and how such changes are reflected in the time series data. Each simulation includes 200 observations. Panel A indicates a white-noise process \((v_t)\) in which the error sequence is normally distributed with a mean of zero and a standard deviation of one. Panel B shows what happens if an ARCH error term is introduced to the white-noise error sequence after time is equal to or over 100. In Panel B, there are outliers and volatilities in the error sequence; thus, the variance is not constant anymore.

Panel C-D indicate how the error structure interacts with autocorrelation parameters of the Y sequences. The ARCH (1) error sequence is introduced to the Y sequence when the autocorrelation parameter of the Y sequence is .3 in Panel C or .9 in Panel D. The changes in the Y sequence become
greater and more persistent when the autoregressive parameter increases from .3 to .9. There is a considerable degree of autocorrelation in the volatility of the Y sequences across time periods. In addition, the Y sequences are not normally distributed, and their variance varies over time.

Two approaches can statistically address the problems of non-normality and heteroscedasticity that often result from omitted variables. First, the Box-Cox power transformation is a useful tool to reduce heteroscedasticity, as well as non-normality in the residuals. The Box-Cox function can be expressed as: \( y^{(\lambda)} = (y^\lambda - 1) / \lambda \) (Box & Cox, 1964; McDowall et al., 2019). It is important to choose the best lambda value (\( \lambda \)) that stabilizes the variance function of a time series. However, the transformed data do not represent the actual data-generating process and lose important information about volatility in the series. It is also difficult to interpret study outcomes in intuitive and consistent manners due to the transformed data.

Alternatively, GARCH modeling can address heteroscedasticity without the need of smoothing data and losing any data generating information. Generalized autoregressive conditional heteroscedastic or GARCH (p, q) models can be written as (Bollerslev, 1986):

\[
h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-1}.
\]

where \( \alpha_0 \) is a constant, \( \varepsilon_{t-i}^2 \) is an ARCH term, and \( h_{t-1} \) is a GARCH term. The stability conditions for the GARCH process are \( p \geq 0, q > 0, \alpha_0 > 0, 0 \leq \alpha_i < 1, 0 \leq \beta_i < 1 \), and \( 0 \leq \alpha_0 + \beta_i < 1 \). Both ARCH and GARCH terms measure how long the effects of a past residual or a past volatility persist and how fast they fade away. The coefficient of the ARCH term is defined as the effect of a one-week lagged, squared residual on current volatility in the series. The GARCH term is interpreted as the effect of one-week lagged volatility on current volatility in the series. GARCH models allow the variance of the residuals to differ over time as a linear function of past squared errors and past variances. Thus, GARCH models estimate the conditional variance of the series, as well as its expected mean.

**Results**

*Models with the Box-Cox Transformation*

Given that all the series were not normally distributed, the research took the Box-Cox power transformation of the series with the best lambda value that minimizes the variance function of each series. The lambda with the highest log-likelihood value was chosen for each dependent variable, as seen in Figure 4 and Tables 3 and 4. Then, this study estimated the models with the transformed data. If there are zero values in the data, this study adds a constant value of one to each value of the dependent variables prior to the Box-Cox transformation. In Tables 3 and 4, the coefficients present the changes in the number of shootings. No multicollinearity was detected in the study because the VIF values for all predictors are less than four (Studenmund, 2014).

*Gun violence by fatality.* As shown in Table 3, there are three transformed outcome variables with the best lambda values: fatal \( \lambda = 0.30 \), non-fatal \( \lambda = 0.30 \), and the total combined shootings \( \lambda = 0.26 \). An examination of the residuals presents no autocorrelation nor heteroscedasticity in all models, and there is evidence of normality. All models manifest significant rises in gun violence during the relaxation of social distancing. Given that all-time series were smoothed with the different lambda values, it is challenging to interpret the outcomes in a consistent manner. For example, during the relaxation of social distancing, there were increases in fatal, non-fatal, and the total combined shootings, on average, by 1.06, 1.47, and 1.56 units of the transformed series. In addition, the BLM variable is
significantly associated with non-fatal and the total combined shootings. The temperature variable is a significant predictor of all outcome variables.

**Gun violence by location.** Table 4 reports the models with the best lambda values: The Bronx $\lambda = 0.22$, Brooklyn $\lambda = 0.10$, Manhattan $\lambda = 0.18$, Queens $\lambda = 0.34$, and Staten Island $\lambda = -1.07$. The residuals of all models are free from autocorrelation and heteroscedasticity. There was normality in the residuals of the models for Brooklyn, Manhattan, and Queens, whereas, despite the Box-Cox transformation, non-normality was still shown for The Bronx and Staten Island due to many zeros and/or spikes in the series. In sum, significant increases in gun violence were detected during the relaxation of social distancing across all boroughs ($p < .01$) but Staten Island ($p < .1$). In addition, the BLM variable is a significant predictor of gun violence for The Bronx only. Temperature is statistically associated with gun violence in all boroughs but Staten Island.

**GARCH Models**

The Box-Cox transformation provides a summary score about the impact of the intervention in terms of direction and significance. However, there are difficulties in interpreting its magnitude. In addition, the smoothed data often lose important information about volatility in the series. As a complement to the Box-Cox transformation method, this study conducts GARCH analyses with the original data to address heteroscedasticity in the residuals of the models for non-fatal and the total combined shootings and for Brooklyn. This methodological approach also allows for analyzing volatile changes in both the mean and variance of gun violence. As shown in Table 5, the best fitting models include: GARCH (1,1) for non-fatal shootings, GARCH (1,1) for the total combined shootings, and GARCH (1,1) for Brooklyn. An examination of the residuals presents no autocorrelation nor heteroscedasticity for all GARCH models. There is evidence of non-normality in the residuals, especially for the total combined shootings and for shootings in Brooklyn. Thus, this study uses quasi-maximum likelihood (QML) covariances and standard errors that are robust to non-normality in the residuals (Bollerslev & Wooldridge, 1992). There is no multicollinearity among the variables.

There were significant increases of 12.89 non-fatal and 17.50 total combined shootings per week during the relaxation of social distancing. For non-fatal shootings, a gradual parameter ($\delta y_{t-1}$) is significant at the conventional level. Thus, the gradually accruing impact of the relaxed SAHO variable on non-fatal shootings was 15.16, or 12.89/(1-.15). The number of non-fatal shootings increased by 12.89 in the first week of the relaxation of social distancing. There was a cumulative increase of 14.824 non-fatal shootings in the second week, 15.113 in the third week, 15.157 in the fourth week, and so on. The number of non-fatal shootings continued to increase at a diminishing rate with each passing week until the impact reached the limit of 15.16. In addition, temperature is significantly related to increases in non-fatal shootings and the total combined shootings. The BLM variable is a significant predictor of non-fatal shootings only at the .1 level.

Given the existence of significant ARCH and GARCH errors for both non-fatal and the total combined shootings, there is still unknown/unmeasurable volatility in the series. The ARCH terms for non-fatal and the total combined shootings are .22 and .27, respectively. The effects of one-week past shocks are not large. Given the large values of the GARCH terms (.66 or .65), the conditional variances are characterized by more autoregressive persistence. Thus, both time series display a high degree of volatility persistence and tend to remain away from their means for long periods of time due to unknown/unmeasurable volatility shocks.

In Brooklyn, there was a significant increase in shootings during the relaxation of social distancing. In addition, both BLM and temperature variables are significant predictors of shootings. In the variance equation for Brooklyn, the ARCH (.28) and GARCH (.57) terms are positive and
significant, fulfilling the conditions for stability. Thus, the conditional variance of shootings in Brooklyn varies over time and depends on the realized value of a past squared error and variance.

**Modeling volatility in Gun violence for optimal decision making.** Policy makers and practitioners might be more interested in the volatility of gun violence over future periods, as opposed to over past periods. GARCH modeling allows us to forecast changes in the conditional variance of shootings, as well as those in expected shootings. This study uses an ex-post out of sample forecast method with one-step ahead predictions. There are two data segments: history (1/3/2016–10/18/2020, 251 observations) and artificial future (10/25/2020–12/27/2020, 10 observations). This study runs GARCH models over the history period and forecasts the mean and the variance of shootings over the artificial future period.

Figure 5 plots the predicted conditional variances of the series, as well as their observed and predicted means. The mean of the total combined shootings decreased and became stabilized over the artificial future period, but the variance of shootings is still variable and fluctuating over time. The level of the total combined shootings is less predictable at the city level, leaving policy makers and local residents uncertain about public safety. On the other hand, there is an overall decrease in the variance of non-fatal shootings at the city level and shootings in Brooklyn over the artificial future period. Declining volatility could mean that the rate of gun violence became stabilized at a certain level. Given that the volatilities of both time series began increasing towards the end of the year, policy makers and practitioners should plan appropriate levels of staffing and resources for law enforcement. Forecast of the conditional variance of gun violence is helpful as it informs a measure of the risk and uncertainty involved in gun violence at particular time periods and the strategic planning process for law enforcement.

**Models with Unemployment Rates**

This study conducted additional analyses since unemployment data are available at the city level. Table 6 reports the models with the best lambda values: fatal $\lambda = 0.34$, non-fatal $\lambda = 0.30$, and the total combined shootings $\lambda = 0.26$. An examination of the residuals presents no autocorrelation nor heteroscedasticity for all the models. The residuals of the model for fatal shootings are normally distributed, while, despite the Box-Cox transformation, those for non-fatal and the total combined shootings still departed from the normal distribution.

Unemployment rates are positively associated with fatal, non-fatal, and the total combined shootings at the .01 significance level. BLM protests are significantly related to non-fatal shootings only, while temperature is a significant determinant of all outcome variables. It is noted that the SAHO Relaxed variable was removed from the models due to its multicollinearity problem with the unemployment variable.

**Discussion and Conclusion**

Several important findings are discussed in line with the research questions and the findings of prior research. First, there were increases in fatal, non-fatal, and the total combined shootings across the city. These findings may echo strain theory. Prior research also presented significant increases in gun violence across U.S. cities (Kim, 2022; Kim & Phillips, 2021; Rosenfeld & Lopez, 2020). Although some studies found no significant change in gun violence (Abrams, 2020; Campedelli et al., 2020), they used very short-term post-intervention observations and overlooked that the impact of the pandemic is realized more gradually. During the pandemic, individuals experienced psychological distress and strain through a range of negative events, such as isolation, unemployment, and limited access to health care and social support. There were increases in alcohol and
gun/ammunition purchases among individuals during the pandemic (Everytown Research & Policy, 2021; Kraviz-Wirtz et al., 2021; Pollard et al., 2020), which might expand opportunities for gun violence. For example, many citizens bought guns and ammunition during the pandemic because they were concerned with lawlessness, prisoner release, the government going too far, government collapse, and gun stores closing (Kraviz-Wirtz et al., 2021, p. 6).

Given that the pandemic had a significant impact on gun violence, regardless of fatalities, there is not much to discuss regarding separate policy implications. However, it is important to note a difficulty in investigating and clearing non-fatal shootings by arrest due to a lack of victim cooperation and resources (Cook et al., 2019; Hipple et al., 2019). Non-fatal shooting victims are often reluctant to call on police and instead take the law into their own hands. Thus, unsolved non-fatal shootings may lead to a cycle of retaliation and gun violence, ultimately resulting in more fatal shootings. Police agencies should make investigative efforts to address non-fatal shootings as vigorously as they handle fatal shootings.

Second, another issue in question is whether such increases in gun violence occurred under SAHO and/or while social distancing was relaxed. In this study, gun violence dramatically increased after the expiration of the SAHO and when individuals began interacting more frequently with one another in the contexts of high unemployment, alcohol consumption, and gun availability. This finding is consistent with routine activity theory. On the other hand, the effects of the SAHO are contingent upon how the models are specified. There were no significant changes in gun violence under the SAHO in the models with the relaxed SAHO variable. However, significant decreases were detected in the models with the unemployment variable, which are consistent with non-US studies presenting significant decreases in homicides during the lockdowns in India (Poblete-Cazenave, 2020) and Peru (Calderon-Anyosa & Kaufman, 2020).

Third, the impact of the BLM protests differs by fatality and location. The impact of the BLM protests is significant for non-fatal shootings ($p < .05$) in most models, echoing Kim and Phillips’ (2021) findings. Thus, the significant increase in non-fatal shootings in May and June might partly result from the riots and crimes associated with the BLM protests. Protestors might be involved as either offenders or victims of gun violence. Specifically, the BLM protests and associated shootings, which usually occurred in public areas, did not influence fatal shootings mostly occurring indoors but instead were significantly associated with non-fatal shootings that are more likely to take place outdoors (see Braga & Cook, 2018). Another finding worthy of discussion is that gun violence associated with the BLM protests was concentrated in The Bronx ($p < .05$) and Brooklyn ($p < .1$) with high minority populations (African Americans and Hispanics). It is reasonable to assume that the BLM protests in minority dominated boroughs were more likely than those in white dominated boroughs to escalate into violence as a result of anger and outrage over the death of George Floyd. In addition, depolicing may be a potential explanation for the increased gun violence (Cassell, 2020). In the absence of active policing in their neighborhoods, motivated offenders were also likely to be empowered and engage in gun violence.

Fourth, the effect of the pandemic varies between urban and suburban boroughs. Unlike other urban boroughs, Staten Island, which is the least populous suburban borough, did not experience a significant increase in shootings during the pandemic at the .05 level. Lower rates of poverty and minority populations in Staten Island are also possible reasons for the non-significant increase in gun violence. The pandemic and social distancing strategies have disproportionately influenced poor racial/ethnic minorities who live in inner cities (Centers for Disease Control and Prevention, 2020). This finding is consistent with Chodos et al.’s (2021) study in which greater increases in firearm-related injury during the pandemic were reported in urban areas, compared to suburban areas. In addition, prior research has found that urban areas have higher rates of violent crime than suburban or rural areas (Duhart, 2000; Gibbs, 1979; Weisheit et al., 1994). It should be noted that the relaxed SAHO variable for Staten Island in the (unreported) model with the original
data was significant at the .01 level, but it lost statistical significance to the .1 level in the model with the Box-Cox transformed data, as seen in Table 4. As previously discussed, the presence of non-normality in the residuals can lead to an incorrect rejection of the null hypothesis. Furthermore, given some evidence of non-stationarity in the series for Staten Island by one out of three unit-root tests (see Table 2), this study conducted an additional (unreported) analysis with the first-order differenced data. None of the SAHO and relaxed SAHO variables are statistically significant. These exhaustive model estimations indicate no significant increase of shootings in Staten Island.

Fifth, the present study has useful information for guiding policy and practice. High unemployment rates are significantly associated with increased gun violence, which is in accordance with the findings of prior research. High crime rates were rooted in chronic unemployment, especially in urban minority neighborhoods (Batton & Jensen, 2002; Carlson & Michalowski, 1997; Fagan & Freeman, 1999; Rosenfeld, 2009; Sampson, 1987). In addition, using data from 16 US cities, Schleimer et al. (2022) found a significant association between unemployment and homicide and gun violence during the pandemic. On the other hand, Kim (2022) presented no impact of unemployment rates on gun violence. It should be noted that the demographic data in Kim’s (2022) study were American Community Survey 5-year estimates, summarizing data from 2014 to 2018. Since unemployment rates are measured prior to the pandemic and time invariant, it could not accurately estimate the impact of changes in unemployment rates on gun violence during the pandemic.

Given the significant increases in unemployment and gun violence during the pandemic, offering social welfare policies is important to weaken the link between unemployment and gun violence when similar disasters occur. Prior studies found that homicide rates are inversely associated with the level of decommmodification (Batton & Jensen, 2002; Messner & Rosenfeld, 1997). The U.S. Congress passed the Coronavirus Aid, Relief, and Economic Security Act, also called CARES Act, to provide economic support for workers and families and help them maintain a socially acceptable standard of living. Future research should examine whether the CARES Act has had any dampening impact on gun violence during the pandemic and why gun violence still significantly increased despite the implementation of the CARES Act.

Sixth, this study used GARCH modeling if heteroscedasticity was detected in the residuals. Models in which the variance of the residuals differ over time violate the assumption of homoscedasticity. This problem often occurs when relevant variables are left out of the statistical models (Engle, 1982). It is thus important to identify as many confounders as possible to adjust for unknown/unmeasurable shocks. In this study, however, the unavailability of weekly data at small geographical units has been an obstacle to understanding the net effect of the pandemic on gun violence, independent of confounders. GARCH modeling is useful for statistically modeling the volatility of gun violence attributable to omitted variables. Using the pseudo-out-of-sample forecasting, this study predicts the number of gun violence and compares it with the actual number that had already occurred. Overall, the actual values lie within the bounds of the 95% confidence interval, presenting the predictions are fairly accurate. In addition, this study predicts the volatility of gun violence. The question of whether gun violence is predictable should be an important policy issue of interest. For example, the volatility of the total combined shootings is highly volatile over the artificial future period. If the levels of gun violence changed rapidly from time to time in an unpredictable manner, it is difficult for policy makers and practitioners to allocate optimal levels of staffing and resources for law enforcement. High volatility also leaves citizens to be more uncertain about public safety and more fearful of crime, which preclude them from establishing stable daily routines. Thus, the need for modeling and forecasting variance is imperative in a volatile and uncertain state of the nation, like the pandemic.

This study fills a gap in the literature by examining whether the pandemic differently facilitated shootings in NYC by social distancing type, fatality, and location, and whether unemployment rates were associated with increased shootings. Both the Box-Cox transformation and GARCH methods
improve the reliability of the study outcomes. Despite its contributions to the literature, there are two shortcomings to the study. Most important is the inability to control for a range of covariates, such as alcohol use, gun purchases, poverty, and inequality. Given that those variables are not readily available at the city level on a weekly basis, this study disaggregated and compared shooting data across five boroughs with different socio-economic characteristics. It also included sufficient pre-intervention time series over four years to control for historical trends. Interrupted time series analysis is a strong quasi-experimental method that uses pre-intervention observations as a control series to reduce internal validity threats originating from history (Cook & Campbell, 1979). Most importantly, GARCH modeling in this study allows for statistically modeling the effects of unknown/unmeasurable factors or shocks on gun violence. Another limitation of the research is the failure to generalize study outcomes across cities. Given its focus on one city, the research findings may not be applicable to other jurisdictions. A wide range of additional data and evaluations are warranted to reach a consensus on the impact of the pandemic on gun violence. In addition, it would be useful if further research uses smaller spatial units, such as census tracts, block groups, and census blocks, to see how the pandemic exerted varying effects on gun violence at micro-spatial levels within a city (see Kim, 2022). It is plausible that particular neighborhoods were more vulnerable to the socio-economic fallouts of the pandemic and experienced greater increases in gun violence.

Research on gun violence is essential and well-timed to reduce the collateral consequences of the pandemic. The current study elucidates a complex picture of gun violence by discussing whether the pandemic had different effects on the mean and variance of gun violence by social distancing type, fatality, and location. It also examines the influence of unemployment rates on gun violence. Finally, it uses the Box-Cox transformation and GARCH methods to reduce the problem of non-normality and/or heteroscedasticity in the residuals, which ultimately increase the reliability of the present study. It is hoped that results learned from this study serve to stimulate future research with a range of data and methods. More research will better inform our decision making about how to reduce gun violence in the volatile state of the nation.

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ORCID iD
Dae-Young Kim https://orcid.org/0000-0002-7932-4627

Notes
1. An ARCH (1) process can be manifested as (Engle, 1982): $\epsilon_t = \nu_t \sqrt{\alpha_0 + \alpha_1 \epsilon_{t-1}^2}$, where $\nu_t$ is a white-noise error, and $\alpha_0$ is set to 1 and $\alpha_1$ to .8 in this study.
2. For exhaustive model estimations, this study conducts additional (unreported) analyses with the T Distribution and the Generalized Error Distribution, which improve the reliability of the study outcomes. Overall, the findings remain similar to those with QML covariances and standard errors in Table 5 in terms of significance, direction, and magnitude.
3. The cumulative effect of the pandemic can be calculated using the equation: $Z_t = \sum_{i=1}^{t} \delta_i^{-\lambda} \omega_0$ (McDowall et al., 2019).
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**Author Biography**

Dae-Young Kim is an associate professor in the Criminal Justice Department at SUNY Buffalo State. His research interests include prisoner reentry, problem-based learning, criminal justice policy and program evaluation, and political economy of crime and punishment. His work has appeared in journals such as Criminal Justice and Behavior, Journal of Criminal Justice, Journal of Crime and Justice, Journal of Experimental Criminology, Journal of Research in Crime and Delinquency, and The Prison Journal.