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Disentangling the Impact of Covid-19: An Interrupted Time Series Analysis of Crime in New York City

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Abstract

The Covid-19 stay-at-home restrictions put in place in New York City were followed by an abrupt shift in movement away from public spaces and into the home. This study used interrupted time series analysis to estimate the impact of these changes by crime type and location (public space vs. residential setting), while adjusting for underlying trends, seasonality, temperature, population, and possible confounding from the subsequent protests against police brutality in response to the police-involved the killing of George Floyd. Consistent with routine activity theory, we found that the SAH restrictions were associated with decreases in residential burglary, felony assault, grand larceny, rape, and robbery; increases in non-residential burglary and residential grand larceny motor vehicle; and no change in murder and shooting incidents. We also found that the protests were associated with increases in several crime types: felony assault, grand larceny, robbery, and shooting incidents. Future research on Covid-19's impact on crime will need to account for these potentially confounding events.

Keywords Covid-19 · Lockdown · Crime · Routine activity theory · Stay-at-home order · Ferguson effect

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Background

To control the transmission of Covid-19, New York City implemented a variety of stay-at-home (SAH) restrictions, closing non-essential businesses, schools, restaurants, and theaters, and barring all non-essential public gatherings (New York State Department of Health, 2020). Routine activity theory (RAT) argues that such changes in day-to-day routines can impact the distribution of crime in a community. The theory posits that predatory crimes against persons or property require three elements—(1) a motivated offender, (2) presence of a suitable target, and (3) the absence of a capable guardian—and that changes in routines related to work, school, and leisure can affect whether these elements come together to create opportunities for crime (Clarke & Felson, 2017; Cohen & Felson, 1979; Felson, 2013). For example, after World War II when people's routines shifted away from the family household and into the labor force and single-family homes, new opportunities for offenders to interact with unguarded targets fueled an increase in crime during the 1950s and 1960s (Cohen & Felson, 1979).

With people shifting more activities into the home during the pandemic, RAT predicts changes in the distribution of crime opportunities depending on the type of crime and location. Specifically, in public settings it predicts fewer opportunities for crime against people (e.g., assault, larceny, robbery) and more opportunities for crime against unguarded property (e.g., car theft, non-residential burglary), while in residential settings it predicts fewer opportunities for crime against property (eg., residential burglary) and more opportunities for crime between members of a residence (e.g., domestic violence). From a RAT perspective, broad changes in the level of various crime types in a community would therefore be expected to coincide with the onset of the SAH restrictions.

Findings from research on the impact of SAH restrictions have generally been consistent with RAT. Typically, researchers have examined the effect of these changes using either interrupted time series analysis, step-ahead ARIMA forecasts, difference-in-differences, or event studies. Table 1 summarizes the findings from studies to date on the impact of SAH restrictions globally. Following the implementation of SAH restrictions, *decreases* were found in *assault* (De la Miyar et al., 2021a, b; Borrion et al., 2020; Gerell et al., 2020; Halford et al., 2020); *robbery* (Estévez-Soto, 2021; Poblete-Cazenave, 2020), *theft* (De la Miyar et al., 2021a, b; Halford et al., 2020; Hodgkinson & Andresen, 2020; Payne et al., 2020; Poblete-Cazenave, 2020), *theft from vehicle* (Halford et al., 2020; Hodgkinson & Andresen, 2020), *residential burglary* (Abrams 2021; Ashby, 2020a, b; Carter & Turner, 2021; Gerell et al., 2020; Halford et al., 2020; Mohler et al., 2020) and *drug crime* (Abrams, 2021), while *increases* were found in *non-residential burglary* (Abrams, 2021; Carter & Turner, 2021; Felson et al., 2020; Hodgkinson & Andresen, 2020; Payne et al., 2020), *car theft* (Abrams, 2021; Mohler et al., 2020) *domestic violence* (Bullinger et al. 2021; Leslie & Wilson, 2020; Mohler et al., 2020; Piquero et al., 2020), *cybercrime* (Buil-Gil et al., 2020), *drug trafficking* (Rashid, 2021), and *shooting incidents* (Kim & Phillips, 2021).

Table 1 Summary of literature

Location(s)	Method(s)	End of study period	Main findings	Author(s)
25 U.S. cities: Atlanta, Austin, Baltimore, Boston, Chicago, Cincinnati, Dallas, Denver, Detroit, Fort Worth, Houston, Los Angeles, Miami, Milwaukee, Minneapolis, Nashville, New York City, Philadelphia, Phoenix, Pittsburg, Portland, San Francisco, Washington, D.C	Difference-in-differences	May 2020	Large and immediate decrease in drug crime, theft, residential burglaries, most violent crimes. Increase in non-residential burglary and car theft. No change in homicides and shootings	Abrams, 2021
10 U.S. cities/areas: Baltimore, Cincinnati, Los Angeles, New Orleans, Phoenix, San Diego, San Jose, Seattle, Sonoma County, St. Petersburg	Step-ahead ARIMA forecasts	May 2020	Overall decline in calls for service	Ashby (2020a)
16 U.S. cities/areas: Austin, Baltimore, Boston, Dallas, Los Angeles, Louisville, Memphis, Minneapolis, Montgomery County, Nashville, Philadelphia, Phoenix, San Francisco, Chicago, Tucson, Washington D.C	Step-ahead ARIMA forecasts	May 2020	Decrease in residential burglary but not non-residential burglary. No change in residential or non-residential serious assaults. Decrease in theft of motor vehicles in some cities	Ashby (2020b)
China (M-1 city)	Forecasting models	April 2020	Decrease in theft followed by an increase	Borrion et al. (2020)
Los Angeles	Step-ahead ARIMA forecasts	September 2020	No change in gang-related crime	Brantingham et al. (2021)
U.K	Mean comparison	May 2020	Increase in cybercrime	Buil-Gil et al. (2020)
Chicago	Difference-in-differences	April 2020	Increase in domestic violence police calls for service	Bullinger et al. (2021)
Peru	Interrupted time series	September 2020	Decrease in homicide	Calderon-Anyosa & Kaufman (2020)

Table 1 (continued)

Location(s)	Method(s)	End of study period	Main findings	Author(s)
Chicago	Structural Bayesian Time Series, Firth's Logistic Regression	May 2020	Community-level differences in effects on crime	Campedelli et al. (2020)
Michigan cities: Detroit, Grand Rapids, Kalamazoo, Lansing	Interrupted time series	December 2020	Decrease in residential burglaries in some cities. Increase in non-residential burglaries in some cities	Carter and Turner (2021)
Mexico City	Event study	May 2020	Decrease in domestic violence, burglary, vehicle theft. Decrease in in assault-battery (in some weeks), extortion	De la Miyar et al. (2021a)
Mexico City	Event study, difference-in-differences	October 2020	Decreases in fraud, assault/battery, theft/property crime, followed by increases back to near baseline levels when mobility recovered. Drug crime, extortion and homicide stable during the pandemic	De la Miyar et al. (2021b)
Mexico City	Step-ahead ARIMA forecasts, crime-mobility models	May 2020	Decrease in violent robbery, non-violent robbery, robbery against residence, violent crime, sexual violence, domestic violence, increase in helpline calls for violence against women. Association between public transit mobility and some crime types	Estévez-Soto (2021)
Detroit	Descriptive	March 2020	Increase in non-residential burglary	Felson et al. (2020)

Table 1 (continued)

Location(s)	Method(s)	End of study period	Main findings	Author(s)
Sweden	Mean comparison	May 2020	Decrease in total crime, indoor and outdoor assault, residential and non-residential burglary, pickpocketing	Gerell et al. (2020)
U.K	Step-ahead ARIMA forecast	April 2020	Decrease in shoplifting, theft, theft from vehicle, assault, domestic abuse, residential burglary, non-residential burglary. Association between changes in mobility and some crime types	Halford et al. (2020)
U.S	Mean comparison, negative binomial regression	April 2020	No change in self-reported cyber-victimization	Hawdon et al. (2020)
Vancouver	Structural break point analysis	May 2020	Decrease in theft, theft from vehicle. Increase in non-residential burglary	Hodgkinson & Andresen (2020)
Buffalo, NY	ARIMA, interrupted time series	October 2020	Short-term increase in fatal shootings and long-term increase in non-fatal shootings	Kim and Phillips (2021)
14 U.S. cities/areas: Baltimore, Chandler, Cincinnati, Detroit, Los Angeles, Mesa, Montgomery County, New Orleans, Phoenix, Sacramento, Salt Lake City, Seattle, Tucson, Virginia Beach	Event study, difference-in-differences	May 2020	Increase in domestic violence	Leslie and Wilson (2020)
Los Angeles, Indianapolis	Interrupted time series	April 2020	Decrease in residential burglary, increase in domestic violence and car theft	Mohler et al. (2020)

Table 1 (continued)

Location(s)	Method(s)	End of study period	Main findings	Author(s)
Miami-Dade County	Geospatial analysis	May 2020	Decrease in violent crimes concentrated in disadvantaged neighborhoods	Moise and Piquero (2021)
27 cities across 23 countries: Amsterdam, Auckland, Barcelona, Brisbane, Cali, Chicago, Hannover, Helsinki, Lima, Ljubljana, London, Malmo, Mendoza, Mexico City, Montevideo, Muzaffarpur, Rio de Janeiro, San Francisco, Sao Paolo, Seoul, Stockholm, Tallinn, Tel Aviv-Yafo, Toronto, Vancouver, Zurich	Interrupted time series, Meta-regression	September 2020	Large decrease in urban crime with variation across cities and crime types. More stringent restrictions were associated with larger decreases in crime	Nivette et al. (2021)
Queensland	Step-ahead ARIMA forecasts	June 2020	Decrease in shop theft, motor vehicle theft, property damage. Short-term increase in non-residential burglary. No change in fraud	Payne et al. (2020)
Dallas	Interrupted time series, step-ahead ARIMA forecasts	March 2020	Increase in domestic violence	Piquero et al. (2020)
India	Regression discontinuity	April 2020	Decrease in murder, theft, robbery, burglary, kidnapping, rioting, crimes against women	Poblete-Cazenave (2020)
Dhaka	Step-ahead ARIMA forecast	September 2020	Sharp increase in drug trafficking, no change in car theft and illegal arms dealing	Rashid (2021)

Table 1 (continued)

Location(s)	Method(s)	End of study period	Main findings	Author(s)
34 U.S cities: Arlington, Atlanta, Austin, Baltimore, Buffalo, Chandler, Chicago, Chula Vista, Cincinnati, Dallas, Denver, Detroit, Jacksonville, Lexington, Lincoln, Long Beach, Los Angeles, Louisville, Madison, Memphis, Milwaukee, Minneapolis, Nashville, New York, Norfolk, Omaha, Philadelphia, Phoenix, Pittsburg, Raleigh, Riverside, Sacramento, San Diego, Seattle, St. Louis, St. Paul, St. Petersburg, Virginia Beach, Washington	Structural break analysis	December 2020	Following SAH restrictions, decreases in domestic violence, nonresidential burglary, drug offenses. Following protests against police violence, increases in homicide, aggravated assault, motor vehicle theft	Rosenfeld et al. (2021)
Japan	Difference-in-differences	May 2020	Decrease in property crime and violent crime with variation by age	Shen et al. (2021)

While a general pattern emerged, important differences were seen across locations, crime types, and time periods. Several studies have attempted to identify the factors that might explain the disparate effects. Nivette et al. (2021) found that locations that imposed more stringent restrictions over movement in public spaces saw larger declines in crime. Brantingham et al. (2021) found that gang-related criminal activities were largely unaffected by the SAH restrictions. Campedelli et al. (2020) found that differences across subcommunities within the same city were associated with a variety of factors, including prior level of crime in a sub-community, perceptions of safety, vacant housing rate, income heterogeneity, poverty, and demographics. Felson et al. (2020) distinguished residential areas from mixed commercial/residential areas and found an increase in burglary only in mixed land use areas. Finally, De la Miyar et al. (2021b) found that the trajectory for less severe crimes (assault, battery, fraud, property crime, theft) followed a U-shaped pattern, falling to a low point about two months after the SAH restrictions and several months later returning back to nearly pre-pandemic levels.

There are several remaining gaps in the research on the impact of the SAH restrictions. First, much of the early research has been limited to the first several months of the pandemic, with several studies having somewhat longer study periods. As SAH restrictions remained in effect beyond this time in many places, studies with longer time periods are needed. Second, studies in the U.S. that extend beyond May 2020 are potentially confounded by the nationwide protests in response to the police-involved killing of George Floyd (Kim & Phillips, 2021; Rosenfeld et al., 2021). In recent years, several such events were followed by an abrupt increase in some crime types, often referred to as the “Ferguson effect,” including robberies (Pyrooz et al., 2016), shootings (Arthur & Asher, 2016; Morgan & Pally, 2016) and murders (Arthur & Asher, 2016; Morgan & Pally, 2016). Research suggests that these increases might be due to a pullback in policing (Devi & Fryer, 2020; Shi, 2009) or the erosion of community trust (Capellan et al., 2020; Rosenfeld, 2016). With longer time series data, it is therefore important to control for the possible history bias caused by these alternative events (Shadish et al., 2002). Third, as Stickle and Felson (2020) have pointed out, when researching crime in a pandemic it is critical to account for place-based differences between residential and non-residential settings. While several studies have accounted for these differences for burglary (Abrams, 2021; Ashby, 2020b; Carter & Turner, 2021; Felson et al., 2020; Gerell et al., 2020; Halford et al., 2020; Hodgkinson & Andresen, 2020; Mohler et al., 2020; Payne et al., 2020) and assault (Gerell et al., 2020), this level of granularity is so far lacking for other crime types.

Current Focus

On March 16, 2020, New York City initiated a series of stay-at-home restrictions to curb the spread of Covid-19. Research on the impact of similar restrictions has shown sharp and immediate changes in the levels of various crime types, broadly consistent with RAT. However, a rigorous analysis of the impact of the restrictions imposed in New York City, the location of one of the U.S.'s most lethal outbreaks (Yang et al., 2021) and strictest lockdowns (Hale et al., 2020), has yet to be conducted. Also, prior research on the impact of similar SAH restrictions has had several limitations, including: (1) short study periods, (2) lack of place-based distinctions for various crime types, and (3) in the U.S. a failure to control for the subsequent protests against police brutality. To address these limitations, this study will estimate the impact of New York City's SAH restrictions on multiple crime types using interrupted time series models. The models will be stratified by incident location to explore place-based differences (public space v. residential) and will include a second breakpoint to account for the subsequent period of protests, allowing us to explore differences in the impact of the SAH restrictions in New York City by crime type, location, and time period.

Data and Methods

Crime Data

Crime incident data were collected from the New York Police Department's (NYPD) open portal (NYPD, 2021).[1] Crime types were classified by the NYPD based on New York State Penal Law (except for rape, which follows the FBI's Uniform Crime Reporting definition). In all, eight crime types were included in the analysis:

- burglary
- felony assault
- grand larceny
- grand larceny motor vehicle
- murder
- rape
- robbery
- shooting incidents

For the period of January 1, 2017, to December 31, 2020, crime incidents were aggregated by day for each crime type. Data on incident location (NYPD's "description of premises" variable) was used to identify whether an incident was carried out in a public space or a residential setting. This was possible for all crime types except murder and shootings, for which the NYPD does not provide premises type information.

[1] Data on burglary, felony assault, grand larceny, grand larceny motor vehicle, rape, and robbery were collected from the NYPD's Incident-level Complaint database. Data on shootings were collected from the NYPD's Incident-level Shooting database. For shootings with multiple victims, the data were de-duplicated to identify unique shooting incidents. Data on homicides were collected from the NYPD's Supplemental Annual Homicide report.

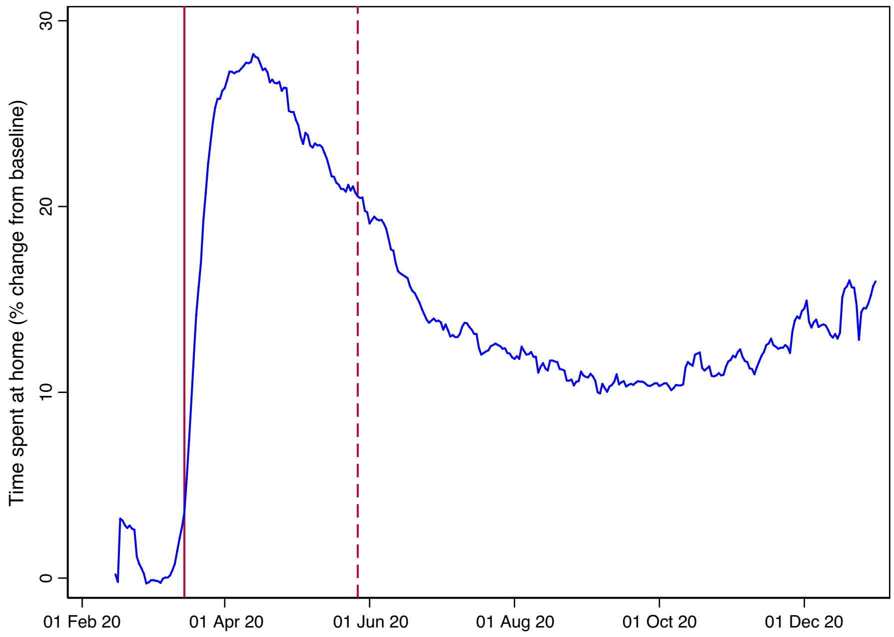

Fig. 1 Google mobility data on time spent at home (February 15, 2020 – December 31, 2020) (Google, 2021). Solid red line indicates the start of the SAH restrictions (March 16, 2020) and the dashed red line indicates the start of the protests against police brutality (May 28, 2020). The measure is calculated based on location history data from Google accounts. Google maps are used to distinguish places of residences from other location types. Beginning on February 15, 2020, the data captures changes in duration at a place of residence compared to a pre-COVID-19 baseline period (the median value from the 5-week period Jan 3 – Feb 6, 2020). Data were aggregated across the five New York City counties. Note that the largest possible change in mobility may only be around 50%, as people already spend much of their time at home

SAH Restrictions

The first SAH restrictions in New York City occurred on March 16, 2020, closing schools, restaurants (except takeout), bars, theaters, and gyms, and limiting public gatherings (Axelson, 2020). According to mobility data from this time, these restrictions caused a dramatic shift in people's routines away from public spaces and into the home (Fig. 1). To measure the impact of these restrictions on crime incidents, we used a dummy variable whereby 0 represents the pre-intervention period (January 1, 2017 – March 15, 2020) and 1 represents the intervention period (March 16, 2020 – December 31, 2020).

Protests against Police Brutality

The police-involved killing of George Floyd sparked sustained nationwide protests against police brutality, which in New York City began on May 28, 2020 (NYC Department of Investigation, 2020). According to data from the Armed Conflict and Location Event Data (ACLED) project, the social unrest continued

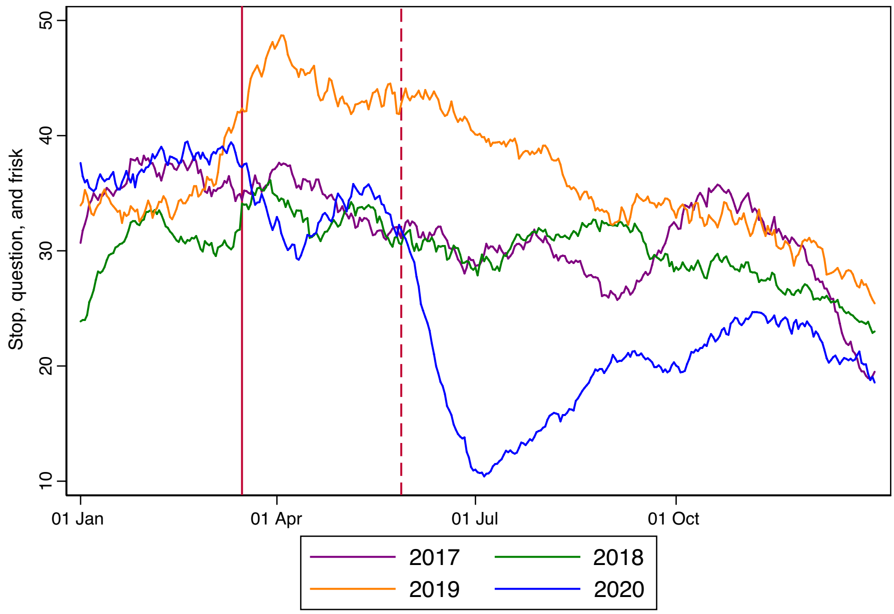

Fig. 2 Stop, Question and Frisk (30-day moving average). Solid red line indicates the start of the SAH restrictions (March 16, 2020) and the dashed red line indicates the start of the protests against police brutality (May 28, 2020). Data were collected from the NYPD's Stop, Question, and Frisk database

until early December, and included a total of 179 Black Lives Matter (BLM) protests against police brutality across New York City (ACLED, 2021).

There are several reasons to expect that events were associated with changes in crime. Prior research has found that similar protests in the past were followed by an increase in multiple crime types (Arthur & Asher, 2016; Morgan & Pally, 2016; Pyrooz et al., 2016). A study of 34 U.S. cities, conducted by the National Commission on Covid-19 and Criminal Justice (NCCCJ), found an association between the start of the protests against police brutality in 2020 and increases in homicide, aggravated assault, and motor vehicle theft (Rosenfeld et al., 2021). That other countries with similar responses to Covid-19 did not see a rise in crime suggests an alternative explanation for such increases in the U.S. (Economist, 2021). Finally, in the aftermath of the protests there was a sharp and sustained pullback in policing for the remainder of 2020, as measured by the frequency of Terry stops (Fig. 2) and arrests (Fig. 3). Thus, to control for the impact of these events, we included a second dummy variable whereby 0 represents the period before the social unrest (January 1, 2017 – May 27, 2020) and 1 represents the period after (May 28, 2020 – December 31, 2020).

Descriptive Analysis

We conducted descriptive analyses for each crime type. The mean and standard deviation of daily counts are presented for each segment of the analysis: the pre-SAH period (January 1, 2017 – March 15, 2020), the post-SAH period (March 16,

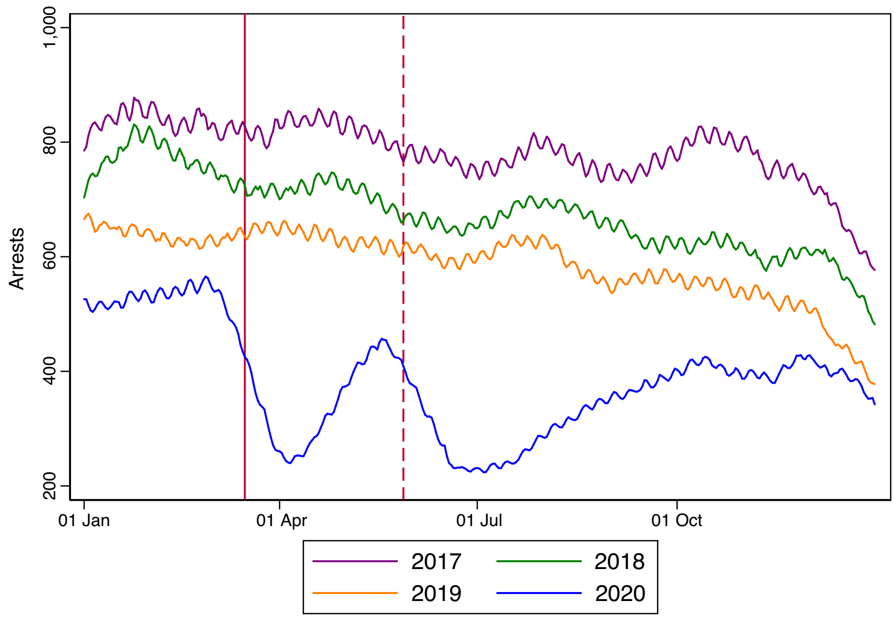

Fig. 3 Arrests (30-day moving average). Solid red line indicates the start of the SAH restrictions (March 16, 2020) and the dashed red line indicates the start of the protests against police brutality (May 28, 2020). Data were collected from the NYPD's Incident-level Arrest database

2020 – May 27, 2020), and the post-protest period (May 28, 2020 – December 31, 2020). For crimes types with location information available (burglary, felony assault, grand larceny, grand larceny motor vehicle, rape, robbery), the descriptive analysis was stratified by location: public space vs. residential.

Interrupted Time Series Analysis

We used interrupted time series (ITS) analysis to estimate the impact of the SAH restrictions on each crime type. In the absence of a randomized-controlled experiment, ITS is considered a strong quasi-experimental alternative (Shadish et al., 2002). Following Nivette et al. (2021), the ITS models were estimated using segmented Poisson generalized linear models with a logit-link function, given the count nature and daily frequency of the crime incident data. Because RAT predicts immediate changes—depending on whether motivated offenders and targets converge at a particular time—we estimated the impact of the SAH restriction on the change in level of multiple crime types (Bernal et al., 2017). For nearly all crime types (burglary, felony assault, grand larceny, grand larceny motor vehicle, rape, robbery), the NYPD provides a description of the location type for each crime incident. Where this information was available, the models were stratified by location.

Table 2 Dickey-fuller test results

	Combined		Public space		Residential	
	Test statistic	MacKinnon *p* value	Test statistic	MacKinnon *p* value	Test statistic	MacKinnon *p* value
Burglary	-22.93	0.00	-20.85	0.00	-33.67	0.00
Felony assault	-25.65	0.00	-24.78	0.00	-31.92	0.00
Grand larceny	-22.07	0.00	-19.17	0.00	-30.36	0.00
Grand larceny MV	-21.01	0.00	-21.69	0.00	-34.75	0.00
Murder	-37.36	0.00				
Rape	-37.38	0.00	-38.66	0.00	-37.86	0.00
Robbery	-26.77	0.00	-26.12	0.00	-35.76	0.00
Shootings	-29.13	0.00				

Critical values 1% = -3.96, 5% = -3.41, 10% = -3.12

Number of observations 1,460

To control for possible confounding due to cyclical crime trends, such as day-of-the week crime patterns and seasonal crime patterns (Andresen & Malleson, 2015; McDowall et al., 2012), dummy variables were included for day-of-the-week, month, and year. Additionally, average daily temperature (°F) was included to adjust for its association with property and violent crime, which has been found to be independent of seasonal fluctuations (Field, 1992; McDowall et al., 2012), Historical weather data was manually retrieved from Weather Underground (Weather Underground, 2021). Based on an inspection of the data, dummy variables were also included for outliers for a particular crime type on a given day (e.g., January 1st).

We took several further steps to ensure the models were appropriately specified. Augmented Dickey-Fuller tests were run to test for a unit-root process (random walk with or without drift) in the time series. For each crime time series, we were able to reject the null that it was generated by a non-stationary process (Table 2).

All models included a population offset based on New York City population estimates for a given year. Population data came from the U.S. Census Bureau (Census, 2021). To address overdispersion, a scaling adjustment was used to produce more conservative estimates of uncertainty (Bernal et al., 2017; Bhaskaran et al., 2013). Finally, to correct for autocorrelation, we examined the ACF and PACF model residual plots, and where indicated included autoregressive term(s) (AR) for lagged values and/or moving average (MA) term(s) for lagged residuals. Akaike information criterion values were used to assess model fit.

Results

We used ITS analysis to estimate the impact of SAH restrictions on multiple crime types in New York City. To account for possible confounding due to the subsequent protests, our models were segmented by two breakpoints to create three periods: the

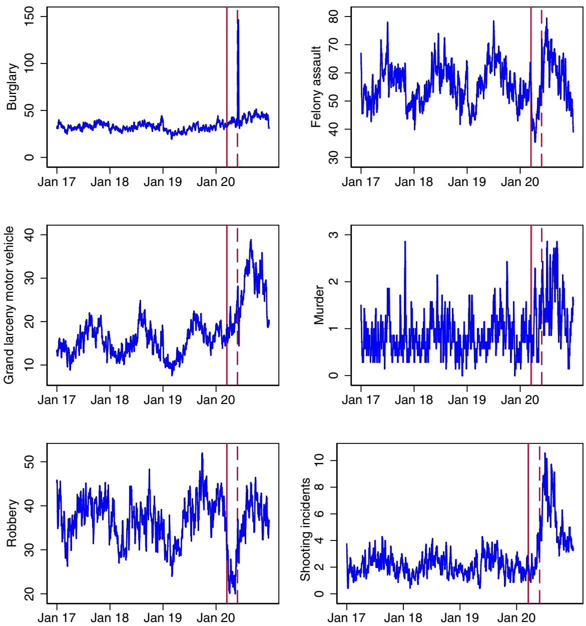

Fig. 4 Crime incidents (7-day moving average). Solid red line indicates the start of the SAH restrictions (March 16, 2020) and the dashed red line indicates the start of the protests against police brutality (May 28, 2020). Data were collected from the NYPD's Incident-level Complaint database

pre-SAH period, the post-SAH period, and the post-protest period. Figure 4 shows the trends for each crime type over the course of these three time periods.

Descriptive statistics across these three time periods are presented for each crime category in Table 3. During the period of the SAH restrictions, the daily average number of incidents decreased for grand larceny (-58.4), robbery (-12.3), felony assault (-11.7), and rape (-2.1), and increased for burglary (+5.4), grand larceny motor vehicle (+4.0) shooting incidents (+0.1), and murder (+0.2). Compared to the post-SAH period, in the post-protest period the daily average number of incidents increased for all crime categories: grand larceny (+32.2), felony assault (+15.1), robbery (+13.0), grand larceny motor vehicle (+9.5), burglary (+8.3), shooting incidents (+3.6), rape (+0.5), murder (+0.5).

Segmented Poisson regression was used to estimate the change in level of multiple crime types following the SAH restrictions, while controlling for underlying trends, seasonality, temperature, population, and possible confounding from the protests against police brutality. Findings from the ITS analyses are presented in Table 4. After the implementation of the SAH restrictions, we found several statistically significant level changes: rape decreased by 40% (IRR = 0.60; 95% CI, 0.45–0.81; $p < 0.01$), grand larceny decreased by 33% (IRR = 0.67; 95% CI, 0.63–0.72; $p < 0.001$), robbery decreased by 32% (IRR = 0.68; 95% CI, 0.63–0.74; $p < 0.001$), and felony assault decreased by 21% (IRR = 0.79; 95% CI, 0.74–0.85; $p < 0.001$). While not the focus of this study, it is notable that there were also several statistically significant level changes following the protests: shootings increased by 96% (IRR = 1.96; 95% CI, 1.59–2.41; $p < 0.001$), robbery increase by 24% (IRR = 1.24; 95% CI, 1.15–1.32; $p < .001$), felony

Table 3 Descriptive statistics

	Pre-SAH Mean(SD)	SAH Mean(SD)	Mean change	Protests Mean(SD)	Mean change
Burglary	32(7.8)	37.4(7.6)	+5.4	45.7(33.4)	+8.3
Felony assault	55.8(12.6)	45.1(10.3)	-11.7	60.2(15.5)	+15.1
Grand larceny	120.8(23.3)	62.4(13.7)	-58.4	94.6(21.1)	+32.2
Grand larceny MV	15.3(5.0)	19.3(5.1)	+4.0	28.8(7.2)	+9.5
Murder	0.8(1.0)	1.0(1.1)	+0.2	1.5(1.4)	+0.5
Rape	4.4(3.6)	2.3(1.6)	-2.1	2.8(1.9)	+0.5
Robbery	37.1(8.1)	24.8(6.9)	-12.3	37.8(8.3)	+13.0
Shooting incidents	2.1(1.7)	2.2(1.7)	+0.1	5.6(3.7)	+3.4

assault increased by 23% (IRR = 1.23, 95% CI, 1.17–1.31; $p < 0.001$), and grand larceny increased by 22% (IRR = 1.22; 95% CI, 1.16–1.29; $p < 0.001$).

Stratified by Incident Location

To examine whether there were place-based differences in the impact of the SAH restrictions, our analyses were stratified by location: public space vs. residential setting. Descriptive statistics across the three relevant time periods are presented in Table 5. In public spaces, during the post-SAH period, the daily average number of incidents decreased for grand larceny (-42.6), robbery (-11.0), felony assault (-8.9), and rape (-0.5), but increased for burglary (+9.0) and grand larceny motor vehicle (+3.1). In residential settings, during the post-SAH period, the daily average number of incidents decreased for grand larceny (-15.0), burglary (-3.5), felony assault (-1.7), rape (-1.6), and robbery (-1.2), but increased for grand larceny motor vehicle (+0.9).

Results from the stratified ITS analyses are presented in Tables 6 and 7. In public spaces, there were several statistically significant level changes: rape decreased by 46% (IRR = 0.54; 95% CI, 0.33–0.88; $p < 0.05$), robbery decreased by 37% (IRR = 0.63; 95% CI, 0.58–0.69; $p < 0.001$), grand larceny decreased by 37% (IRR = 0.63; 95% CI, 0.59–0.68; $p < 0.001$), felony assault decreased by 34% (IRR = 0.66; 95% CI, 0.59–0.73; $p < 0.001$), and burglary increased by 28% (IRR = 1.28; 95% CI, 1.15–1.42; $p < 0.001$). In residential settings, there were also several statistically significant level changes: rape decreased by 30% (IRR = 0.70; 95% CI, 0.49–0.99; $p < 0.05$), grand larceny decreased by 24% (IRR = 0.76; 95% CI, 0.68–0.84; $p < 0.001$), burglary decreased by 14% (IRR = 0.86; 95% CI, 0.78–0.95; $p < 0.05$), felony assault decreased by 10% (IRR = 0.90; 95% CI, 0.83–0.98; $p < 0.05$), and grand larceny motor vehicle increased by 67% (IRR = 1.67; 95% CI, 1.22–2.28; $p < 0.01$).

Discussion

To curtail the spread of Covid-19, New York City imposed one of the most stringent lockdowns in the U.S. (Hale et al., 2020). The ensuing shift in day-to-day routines created one instance of what Stickle and Felson (2020) describe as the largest

Table 4 Segmented Poisson regression results

	Burglary		Felony assault		Grand larceny		Grand larceny MV		Murder		Rape		Robbery		Shooting incidents	
	IRR	SE	IRR	SE	IRR	SE	IRR	SE	IRR	SE	IRR	SE	IRR	SE	IRR	SE
Interruption																
SAH	1.07	(0.04)	0.79***	(0.03)	0.67***	(0.02)	1.09	(0.05)	1.09	(0.23)	0.60**	(0.09)	0.68***	0.03	1.03	0.15
Protests	1.01	(0.03)	1.23***	(0.04)	1.22***	(0.03)	1.03	(0.04)	1.34	(0.22)	1.10	(0.14)	1.24***	0.04	1.96***	0.21
Year																
2017 (ref)																
2018	0.79	(0.18)	1.07	(0.20)	1.34	(0.22)	0.45**	(0.12)	2.50	(3.08)	316.10***	(244.69)	0.60*	0.13	0.93	0.69
2019	0.58	(0.26)	1.12	(0.42)	1.65	(0.54)	0.20**	(0.11)	6.72	(16.52)	67,631.14***	(104,563.00)	0.39*	0.17	0.95	1.39
2020	0.61	(0.40)	1.21	(0.68)	2.25	(1.10)	0.12*	(0.10)	18.51	(68.12)	1.77e+07***	(4.10e+07)	0.28*	0.18	1.05	2.30
Month																
January (ref)																
February	0.91**	(0.03)	0.95*	(0.03)	1.01	(0.02)	0.88**	(0.04)	0.96	(0.18)	1.71***	(0.20)	0.90**	0.03	0.71**	0.09
March	0.83***	(0.04)	1.01	(0.04)	1.02	(0.03)	0.78***	(0.05)	0.94	(0.24)	2.72***	(0.43)	0.78***	0.03	0.77	0.12
April	0.86*	(0.05)	0.94	(0.05)	1.04	(0.05)	0.73***	(0.06)	1.17	(0.41)	4.78***	(1.04)	0.73***	0.04	0.75	0.16
May	0.82*	(0.07)	1.02	(0.07)	1.08	(0.06)	0.73**	(0.07)	1.21	(0.54)	7.67***	(2.14)	0.75***	0.06	0.74	0.20
June	0.77**	(0.08)	0.97	(0.08)	1.10	(0.08)	0.69**	(0.09)	1.27	(0.70)	12.32***	(4.23)	0.69***	0.07	0.73	0.24
July	0.83	(0.10)	0.93	(0.09)	1.13	(0.10)	0.74*	(0.11)	1.52	(0.98)	19.92***	(8.10)	0.65***	0.07	0.71	0.27
August	0.85	(0.11)	0.93	(0.11)	1.16	(0.12)	0.76	(0.13)	1.48	(1.10)	30.70***	(14.35)	0.66**	0.09	0.73	0.32
September	0.82	(0.12)	0.93	(0.12)	1.23	(0.14)	0.67*	(0.13)	1.73	(1.45)	53.85***	(28.36)	0.67**	0.10	0.64	0.32
October	0.86	(0.15)	0.96	(0.14)	1.27	(0.16)	0.65*	(0.14)	1.74	(1.62)	78.58***	(46.09)	0.68*	0.11	0.69	0.38
November	0.84	(0.16)	0.97	(0.15)	1.32*	(0.18)	0.60*	(0.14)	1.50	(1.55)	128.18***	(83.09)	0.67*	0.12	0.69	0.42
December	0.86	(0.18)	1.00	(0.17)	1.36*	(0.20)	0.55*	(0.14)	1.80	(2.03)	201.68***	(143.57)	0.68*	0.13	0.90	0.61

Table 4 (continued)

	Burglary		Felony assault		Grand larceny		Grand larceny MV		Murder		Rape		Robbery		Shooting incidents	
	IRR	SE	IRR	SE	IRR	SE	IRR	SE	IRR	SE	IRR	SE	IRR	SE	IRR	SE
Day of week																
Sunday (ref)																
Monday	1.25***	(0.03)	0.82***	(0.01)	1.27***	(0.02)	1.03	0.03	0.80*	(0.09)	0.79***	(0.05)	1.00	0.02	0.75***	0.05
Tuesday	1.23***	(0.03)	0.78***	(0.01)	1.21***	(0.02)	1.01	0.03	0.88	(0.09)	0.73***	(0.05)	0.94**	0.02	0.68***	0.04
Wednesday	1.26***	(0.03)	0.82***	(0.01)	1.23***	(0.02)	1.00	0.03	0.83	(0.09)	0.71***	(0.05)	0.93***	0.02	0.63***	0.04
Thursday	1.26***	(0.03)	0.78***	(0.01)	1.20***	(0.02)	1.00	0.03	0.76	(0.08)	0.77***	(0.05)	0.92***	0.02	0.60***	0.04
Friday	1.47***	(0.03)	0.85***	(0.02)	1.31***	(0.02)	1.09**	0.03	0.76*	(0.08)	0.84**	(0.06)	0.96*	0.02	0.75***	0.05
Saturday	1.18***	(0.03)	1.00	(0.02)	1.13***	(0.02)	1.01	0.03	1.06	(0.11)	0.99	(0.06)	1.02	0.02	0.95***	0.06
Temperature	1.00***	(0.00)	1.01***	(0.00)	1.00***	(0.00)	1.01***	0.00	1.01	(0.00)	1.00	(0.00)	1.01***	0.00	1.02***	(0.00)
Time	1.00	(0.00)	1.00	(0.00)	1.00	(0.00)	1.00**	0.00	1.00	(0.00)	0.98***	0.00	1.00*	0.00	1.00	(0.00)
AIC	6.71		7.46		8.97		5.81		2.59		4.78		6.80		3.72	
Q-statistic	6.99		4.40		13.66		15.31		6.48		8.34		14.22		15.23	

Models also include lagged dependent values (AR terms) or lagged residual values (MA terms) where appropriate, and dummy variables for outliers on a given day.

* $p<0.05$

** $p<.01$

*** $p<0.001$

Table 5 Descriptive statistics by incident location

	Public Space					Residential				
	Pre-SAH	SAH		Protests		Pre-SAH	SAH		Protests	
	Mean(SD)	Mean(SD)	Mean change	Mean(SD)	Mean change	Mean(SD)	Mean(SD)	Mean change		Mean change
Burglary	12.5(4.4)	21.5(5.9)	+9.0	26.3(32.9)	+4.8	19.3(5.7)	15.8(4.7)	-3.5	19.2(5.6)	+3.4
Felony assault	26.8(8.4)	17.9(6.1)	-8.9	30.5(10.6)	+12.6	28.9(7.2)	27.2(6.4)	-1.7	29.7(7.6)	+2.5
Grand larceny	81.4(15.1)	38.8(8.7)	-42.6	64.7(15.1)	+25.9	38.5(12.3)	23.5(7.6)	-15.0	29.7(9.6)	+6.3
Grand larceny MV	14.0(4.6)	17.1(4.7)	+3.1	26.5(6.9)	+9.4	1.3(1.2)	2.2(1.5)	+0.9	2.2(1.6)	-
Rape	1.0(1.1)	0.5(0.7)	-0.5	0.7(0.9)	+0.2	3.4(3.2)	1.8(1.4)	-1.6	2.1(1.6)	+0.3
Robbery	29.3(7.3)	18.3(5.5)	-11.0	30.7(7.4)	+12.4	7.7(2.9)	6.5(2.9)	-1.2	7.1(2.7)	+0.6

Table 6 Segmented Poisson regression results: Public space

	Burglary		Felony assault		Grand larceny		Grand larceny MV		Rape		Robbery	
	IRR	SE	IRR	SE	IRR	SE	IRR	SE	IRR	SE	IRR	SE
Interruption												
SAH	1.26**	0.11	0.66***	0.03	0.63***	0.02	1.05	0.05	0.54*	0.13	0.63***	0.03
Protests	1.01	0.07	1.49***	0.06	1.27***	0.04	1.07	0.04	1.31	0.28	1.31***	0.05
Year												
2017 (ref)												
2018	1.77	0.96	0.90	0.24	1.06	0.17	0.43**	0.12	26.99**	33.81	0.54*	0.13
2019	2.60	2.82	0.84	0.45	1.04	0.33	0.18**	0.11	503.22*	1259.41	0.32*	0.15
2020	6.86	11.15	0.81	0.64	1.15	0.54	0.11*	0.10	13,022.24*	48,820.83	0.22*	0.16
Month												
January (ref)												
February	1.05	0.09	0.93	0.04	0.99	0.02	0.88**	0.04	1.59*	0.31	0.87***	0.03
March	1.05	0.12	0.98	0.05	0.96	0.03	0.79***	0.05	1.80*	0.47	0.75***	0.04
April	1.21	0.19	0.89	0.07	0.96	0.04	0.72***	0.06	3.02**	1.07	0.70***	0.05
May	1.35	0.27	0.99	0.10	0.98	0.06	0.71**	0.08	3.26*	1.49	0.72***	0.06
June	1.70	0.41	0.89	0.11	0.98	0.07	0.67**	0.09	3.84*	2.16	0.66***	0.07
July	1.67	0.48	0.85	0.12	0.98	0.08	0.72*	0.11	5.03*	3.34	0.61***	0.08
August	1.77	0.58	0.85	0.14	0.99	0.10	0.73	0.13	7.82*	5.95	0.62**	0.09
September	1.78	0.66	0.85	0.15	1.04	0.11	0.64*	0.13	11.67**	9.98	0.62**	0.10
October	1.84	0.76	0.88	0.18	1.06	0.13	0.62*	0.14	12.97**	12.34	0.65*	0.12
November	1.80	0.82	0.85	0.19	1.08	0.14	0.58*	0.14	19.30**	20.28	0.63*	0.13
December	1.88	0.94	0.84	0.21	1.09	0.16	0.53*	0.14	18.30*	21.14	0.62*	0.14

Table 6 (continued)

	Burglary		Felony assault		Grand larceny		Grand larceny MV		Rape		Robbery	
	IRR	SE	IRR	SE	IRR	SE	IRR	SE	IRR	SE	IRR	SE
Day of week												
Sunday (ref)												
Monday	1.38***	0.07	0.82***	0.02	1.09***	0.02	1.04	0.03	0.71**	0.08	1.02	0.02
Tuesday	1.14*	0.06	0.78***	0.02	1.06***	0.02	1.01	0.03	0.63***	0.07	0.98	0.02
Wednesday	1.15**	0.06	0.83***	0.02	1.08***	0.02	1.01	0.03	0.63***	0.07	0.96	0.02
Thursday	1.16**	0.06	0.78***	0.02	1.08***	0.02	1.02	0.03	0.77*	0.08	0.94**	0.02
Friday	1.38***	0.07	0.90***	0.02	1.19***	0.02	1.09**	0.03	0.72**	0.08	0.98	0.02
Saturday	1.10	0.06	1.04***	0.02	1.09***	0.02	1.02	0.03	0.87	0.09	1.02	0.02
Temperature	1.00	0.00	1.01***	0.00	1.00***	0.00	1.01***	0.00	1.01*	0.00	1.01***	0.00
Time	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00	0.99*	0.00	1.00*	0.00
AIC	6.66		6.65		7.80		5.71		2.55		6.56	
Q-statistic	4.37		5.92		14.32		15.21		12.78		16.87	

Models also include lagged dependent values (AR terms) or lagged residual values (MA terms) where appropriate, and dummy variables for outliers on a given day.

* $p<0.05$

** $p<.01$

*** $p<0.001$

Table 7 Segmented Poisson regression results: Residential setting

	Burglary		Felony assault		Grand larceny		Grand larceny MV		Rape		Robbery	
	IRR	SE	IRR	SE	IRR	SE	IRR	SE	IRR	SE	IRR	SE
Interruption												
SAH	0.86**	0.04	0.90*	0.04	0.76***	0.04	1.67**	0.27	0.70*	0.13	0.88	0.06
Protests	1.09*	0.05	1.07*	0.04	1.14**	0.05	0.69**	0.08	1.04	0.16	1.00	0.06
Year												
2017 (ref)												
2018	1.00	0.28	1.23	0.29	2.78***	0.80	0.64	0.58	1510.62***	1391.28	0.86	0.35
2019	1.00	0.56	1.43	0.67	6.89**	3.93	0.43	0.79	1,521,806.00***	2,799,312.00	0.80	0.65
2020	1.19	1.00	1.72	1.21	18.44**	15.75	0.36	0.98	1.69e+09***	4.66e+09	0.77	0.93
Month												
January (ref)												
February	0.89**	0.04	0.96	0.03	1.09*	0.04	0.82	0.12	1.59**	0.22	1.01	0.06
March	0.83**	0.05	1.03	0.05	1.20**	0.07	0.67*	0.13	2.94***	0.55	0.90	0.07
April	0.86	0.07	0.99	0.07	1.30**	0.10	0.81	0.22	5.64***	1.45	0.82	0.09
May	0.82*	0.08	1.06	0.09	1.41**	0.14	0.89	0.30	11.05***	3.65	0.85	0.12
June	0.77*	0.10	1.06	0.11	1.51**	0.19	0.97	0.40	21.04***	8.56	0.81	0.15
July	0.85	0.13	1.02	0.13	1.67**	0.25	0.99	0.48	39.11***	18.89	0.82	0.18
August	0.90	0.15	1.00	0.14	1.84***	0.32	1.23	0.69	64.46***	35.83	0.88	0.22
September	0.88	0.17	1.00	0.16	2.02***	0.39	1.08	0.68	126.03***	78.96	0.87	0.24
October	0.97	0.21	1.02	0.18	2.16***	0.47	0.98	0.68	212.38***	148.24	0.83	0.26
November	0.98	0.23	1.09	0.22	2.42***	0.58	0.80	0.61	377.40***	291.19	0.85	0.29
December	1.03	0.27	1.15	0.25	2.68***	0.71	0.78	0.66	722.78***	612.22	0.96	0.36

Table 7 (continued)

	Burglary		Felony assault		Grand larceny		Grand larceny MV		Rape		Robbery	
	IRR	SE	IRR	SE	IRR	SE	IRR	SE	IRR	SE	IRR	SE
Day of week												
Sunday (ref)												
Monday	1.27***	0.03	0.81***	0.02	1.70***	0.05	0.93	0.08	0.82*	0.06	0.92*	0.03
Tuesday	1.27***	0.03	0.77***	0.02	1.58***	0.05	1.01	0.08	0.74***	0.06	0.85***	0.03
Wednesday	1.33***	0.04	0.79***	0.02	1.59***	0.05	0.95	0.08	0.70***	0.06	0.87***	0.03
Thursday	1.34***	0.04	0.78***	0.02	1.56***	0.05	0.85*	0.07	0.74***	0.06	0.88***	0.03
Friday	1.53***	0.04	0.80***	0.02	1.64***	0.05	1.07	0.09	0.85*	0.07	0.90**	0.03
Saturday	1.21***	0.03	0.97	0.02	1.20***	0.03	0.94	0.08	0.99	0.07	1.03	0.04
Temperature	1.00***	0.00	1.00***	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00
Time	1.00	0.00	1.00	0.00	1.00**	0.00	1.00	0.00	0.98***	0.00	1.00	0.00
AIC	6.05		6.51		7.61		3.06		4.57		4.88	
Q-statistic	7.87		5.76		6.57		4.32		6.91		11.38	

Models also include lagged dependent values (AR terms) or lagged residual values (MA terms) where appropriate, and dummy variables for outliers on a given day.

* $p < 0.05$

** $p < .01$

*** $p < 0.001$

criminological experiment in history. Relying on routine activity theory, we predicted that the SAH restrictions would impact the level of crime depending on the crime type and location. Prior research has shown dramatic changes in the distribution of crime following the implementation of SAH restriction in locations across the globe. However, to date no rigorous study has been conducted on the impact of SAH restrictions in New York City. Moreover, earlier research has had several important limitations, including short study periods, lack of place-based distinctions for various crime types, and in the U.S. a lack of control for possible confounding from the subsequent protests against police brutality. To address these limitations, we used ITS analysis to estimate the impact of the SAH restriction on multiple crime types in New York City, while adjusting for underlying trends, seasonality, temperature, population, and possible confounding from the subsequent protests. The analyses were then stratified by incident location.

There was considerable variation in the impact of the SAH restrictions by crime type and location. For burglary, there was no change in the aggregate, but broken down by location there was a 26% increase in public spaces and a 14% decrease in residential settings. For felony assault, there was a 21% decrease in the aggregate, and broken down by location a 34% decrease in public spaces and a 10% decrease in residential settings. For grand larceny, there was a 33% decrease in the aggregate, and broken down by location a 37% decrease in public spaces and a 24% decrease in residential settings. For grand larceny motor vehicle, there was no change in the aggregate, and broken down by location a 67% increase in residential settings only. For murder, there was no change (data was not available for stratified analysis). For rape, there was a 40% decrease in the aggregate, and broken down by location a 46% decrease in public spaces and a 30% decrease in residential settings. For robbery, there was a 32% reduction in the aggregate, and broken down by location a 37% decrease in public spaces only. For shooting incidents, there was no change (data was not available for stratified analysis).

There were also several notable increases in the level of crime in the period following the protests against police brutality: shootings (96%), robbery (24%), felony assault (23%), grand larceny (22%), and grand larceny motor vehicle (8%). It is possible that some of these changes represent a regression back to pre-pandemic levels due to rising mobility, as was seen in Mexico City's U-shaped crime recovery (De la Miyar et al., 2021b). However, this is a less plausible when it comes to the increase in shooting incidents, which were unaffected by the SAH restrictions and then rose sharply following the protests. One possibility is that both of these events had an independent effect on crime, as Kim & Phillips (2021) found for certain kinds of shooting incidents. More research is needed to tease apart the impact of these two events, as well as to examine other factors that may have played a role (e.g., the increased sale of firearms in 2020; Economist, 2021).

Overall, our findings contribute to the literature on the effect of SAH restrictions and crime in several ways. First, our findings suggest that SAH restrictions impacted crime by shifting the distribution of suitable targets. With fewer people to target on city streets, we found decreases in predatory crimes commonly committed against individuals in public places: felony assault, grand larceny, rape, and robbery. Importantly, these effects were found either exclusively in public spaces, as was the case with robbery, or to have a much greater magnitude in public spaces compared to residential settings, as was the case with felony assault, grand larceny, and rape. Second, our findings suggest that SAH restrictions impacted crime by displacing capable guardianship. With fewer potential guardians in the streets but more in residences, we found a divergent impact on burglary: an increase in public spaces but a decrease in residential settings. Third, this was the first study to find an increase in grand larceny motor vehicle incidents exclusively in residential settings, despite the increased presence of capable guardians in and around homes. We suspect that this was simply because there were a greater number of cars parked in residential settings after the lockdown, or as Willie Sutton would have put it, “that’s where the cars were.” Fourth, we found that SAH restrictions had no impact on either murder or shooting incidents. This was likely due to the fact that such crimes are often connected with gang-related activity (National Gang Center, 2020), which remained stable throughout the pandemic (Brantingham et al., 2021; Rashid, 2021). Finally, the findings lend credence to our concern about confounding from the protests against police brutality, as these events were followed by immediate changes in the level of multiple crime types.

Limitations

Several limitations of this paper are worth noting. First, we used reported incidents as our measure of crime. Thus, one concern is whether the crime declines we saw reflect a true change or an artifact of hesitancy to report (For a lengthy discussion of why the changes are unlikely to be an artifact of hesitancy to report, see Abrams, 2021). Second, changes in key elements of routine activity theory were not directly measured, but instead were presumed given the dramatic increase in time spent at home following the SAH order. Third, several crime types that might have been affected by changes in routine activity were not included in this study, such as cybercrime, drug crime, domestic violence, and subway crime. Future studies are needed to evaluate the impact of SAH restrictions on these crime types in New York City. Fourth, while we found that the protests against police brutality were temporally associated with increases in several crime types, it is possible that the circumstances created by the SAH restrictions also played a causal role. More research is needed to disentangle the impact of these two causes. Fifth, though New York City provided a unique opportunity to study the effect of stringent SAH restrictions during a very lethal outbreak, it is unclear how generalizable the findings are to other locations. Future research is needed to identify factors responsible for any variation found in the impact of SAH restrictions across geographic locations. Finally, though routine activity theory proved useful as a framework, we have no doubt that other theories can be used to better understand Covid-19’s impact on crime.

Conclusions

The broad stay-at-home restrictions imposed in New York City were followed by an abrupt shift in movement. Consistent with routine activity theory, we found that these changes were associated with decreases in residential burglary, felony assault, grand larceny, rape, robbery; increases in non-residential burglary and residential grand larceny motor vehicle; and no change in murder and shooting incidents. Several months after the start of the SAH restrictions, New York City experienced sustained and mass protests against police brutality followed by a sharp drop in the frequency of Terry stops and arrests. We found that these events were associated with increases in several crime types: felony assault, grand larceny, robbery, and shooting incidents. Future research on Covid-19's impact on crime will need to account for these potential confounding events.

Data Availability Datasets used in the analysis can be made available.

Code Availability Code used in the analysis (Stata do files) can be made available.

Declarations

Conflicts of Interest None to declare.

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