Journal of Criminology and Criminal Justice Studies
Vol. 3, No. 1, 2025, pp. 105-143 • ISSN: 2583-9918

URL: www.arfjournals.com
https://doi.org/10.47509/JCCJS.2025.v03i01.05

A Socio-Ecological Examination of Crime in an Urban Context During the Early Pandemic

***Marika Dawkins-Cavazos[1], Xinyue Ye[2], Camille Gibson[3], Chunwu Zhu[4] and Cuiling Liu[5]**

[1]The University of Texas Rio Grande Valley, Department of Criminal Justice, Edinburg, Texas, U.S.A. E-mail: marika.dawkins@utrgv.edu
[2]Texas A&M University, Department of Landscape Architecture and Urban Planning, College Station, Texas, U.S.A. E-mail: xinyue.ye@tamu.edu
[3]Prairie View A& M University, College of Juvenile Justice, Prairie View, Texas, U.S.A. E-mail: cbgibson@pvamu.edu
[4]M.S., Texas A&M University, Department of Landscape Architecture and Urban Planning, College Station, Texas, U.S.A. E-mail: chunwu.zhu@tamu.edu
[5]Texas A&M University, Department of Landscape Architecture and Urban Planning, College Station, Texas, U.S.A. E-mail: cliu36@tamu.edu
**Corresponding author*

To Cite this Article

Marika Dawkins-Cavazos, Xinyue Ye, Camille Gibson, Chunwu Zhu & Cuiling Liu (2025). A Socio-Ecological Examination of Crime in an Urban Context During the Early Pandemic. *Journal of Criminology and Criminal Justice Studies,* 3: 1, pp. 105-143. *https://doi.org/10.47509/JCCJS.2025.v03i01.05*

Abstract: Many urban areas in the United States saw increased crime during the COVID-19 pandemic. City leaders and criminal justice scholars have shown interest in exploring the connections between the pandemic and crime rates, seeking to identify potential preventive strategies for the future. Toward having such insight, this study examined crimes and signs of disorder during the strictest lockdown year of 2020 in the United States's most diverse and fourth-largest city, Houston. It focused on certain neighborhood characteristics that are indicative of social disorganization and how such characteristics were predictive of changes in crime and disorder; the extent to which guardianship, which is inherent in routine activity theory, was predictive of crime and disorder and to what extent different segments of the population experienced crime and disorder early in the pandemic? Using Houston Police Department's publicly available crime statistics and comparison data from other public community profile sources Negative Binomial Models were run and the data were further examined via geographic information systems mapping. The findings suggest situational crime prevention strategies may be effective. Specifically, prevention policies should include a) an understanding of the lives and motivations of those most likely to be perpetrators and, or victims of crimes and b) an understanding of the ecological dynamics that are likely to bring perpetrators into the realm of opportunities for crime that they are likely to exploit.

Received : 02 January 2025 • **Revised :** 29 January 2025 • **Accepted :** 05 February 2025 • **Published :** 25 June 2025

Introduction

Undoubtedly, the COVID-19 pandemic has had profound consequences on society, including crime. While the relationship between the COVID-19 pandemic and crime is relatively new and complex, its association has become a focus of recent research inquiries. The global impact of the COVID-19 pandemic on people's lives and crime trends varied by person and place, and relatedly the types of crimes committed and overall crime rates, the unique characteristics of a city, place, population, and/or region may also influence how it is impacted by COVID-19. Therefore, this study aims to contribute to current research by focusing on one major urban area in the United States to see what changes in crime, if any, can be attributed to the COVID-19 pandemic.

The pandemic offers rather unique dynamics for novel insights into the occurrence of crime. Initial studies (see, e.g., Ashby *et al*., 2020; Boman & Gallup, 2020; Campedelli, *et al*., 2020; Estévez-Soto, 2021; Nevette, *et al*., 2021; Yang, *et al*., 2021) following the pandemic suggest that the COVID-19 pandemic led to a decrease in crime and more recent studies (see, e.g., Liu *et al*., 2022; Meyer *et al*., 2022; Rosenfeld & Lopez, 2021) suggest that the impact of the COVID-19 pandemic on crime is more complex, not uniform, and worthy of further examination. This is because the impact of the COVID-19 pandemic is still not fully understood. The severity and duration of the pandemic, socio-economic factors, and intervention strategies that were implemented all play a role in helping to shape deviant and criminal behavior.

Like many other cities and places, the pandemic has had a major impact on Houston, Texas. Specifically, it has impacted people's daily routines (e.g., requiring many to work remotely, prohibiting attending establishments – restaurants, nightclubs, bars, sporting events, etc.) given non-essential movement restrictions during the early months. The closure of public places that tend to have large gatherings which increase the likelihood of violence and other victimizations contributed to crime declines. However, from 2019 to 2022, crimes such as domestic violence homicide doubled in Houston as persons spent more time together in residential spaces (Gregory *et al*., 2023). By 2023, post all COVID restrictions these numbers have returned to pre-COVID restriction levels. The initial effects of the COVID-19 pandemic seem to support the tenets of routine activity theory (Felson *et al*., 2020). This study offers insights into these local dynamics in a major United States city, Houston.

Among the common explanations of the occurrence of crime are variables such as disorder, structural characteristics of areas/places, opportunity, and the effectiveness of available social institutions. While any one factor or theory does not adequately explain crime or even variations in crime, it is evident that certain factors (e.g., signs of disorder) facilitate its occurrence. These items reflect aspects of social disorganization theory, concentric zones theory, routine activities theory, and broken windows theory. While it is generally agreed that poverty, inequality, and racial inequality impact crime (Ousey, 2000), the related impacts of physically deteriorated residential communities and a shortage of stable housing characterize high-risk areas (see, e.g., Parker *et al.*, 1925; Shaw & McKay, 1942; Skogan, 2012). Homicide trends during the restrictions have already been examined in the literature (see, e.g., Gramlich, 2021; Mekouar, 2022; Meyer *et al.*, 2022), so this study focuses on other crimes of concern (aggravated assault, burglary, motor vehicle theft, and robbery) and signs of disorder (utilizing 311 calls for nuisance on the property, dead animal collection, sewer wastewater issues, and garbage-related calls). Disorder is included because it is highly correlated with crime (see, e.g., O'Brien, 2019; Wheeler & Reuter, 2020).

In the next section, we delve into the broader crime and place literature and plausible theoretical explanations for crime and COVID-19 in Houston, Texas. A brief geographical context and crime of Houston is first presented to facilitate the theoretical explanations.

Literature Review

Geographical Context and Crime

Houston has a population of over 2.3 million and is designated as the fourth most populous city in the U.S. It is racially and ethnically diverse, with a minimum of 145 languages spoken and immigrants from 90 nations represented (City of Houston, 2022). Nearly a third of the city's population is foreign-born (28.9%) and over 80% of its population commutes to and from work. Compared to other cities in the U.S., Houstonians are well educated, with over 34% of adults having at least a bachelor's degree versus just over 21% of adults in other comparable cities and towns (Location Inc., 2022).

Regarding crime in Houston, violent and property crimes are higher than in cities of similar sizes in Texas (e.g., Austin, Dallas, Fort Worth, and San Antonio). For example, the violent crime rate in Houston is 12.82 versus 4.5 per 1,000 in Texas, while property crime is almost twice the rate of Texas' average (43.06 versus 22.6 per 1,000). Reports suggest there is a one in 78 chance of becoming a victim of a violent crime in Houston versus one in 222 in Texas and one in 23 chances of becoming a victim of property crime in Houston versus one in 44 chances in Texas (Location Inc., 2022). Given crime concerns in Houston, recent crime data before and during COVID-19 are examined to help contextualize the crime problem by examining data that are more likely to have early settled or accurate initial counts. Houston (Hastings-Blow, 2022), much like Los Angeles (Peterson, 2016) is a place where a high concentration of poverty and minority residents near crime scenes negatively impacts the presence or rate of media crime coverage and perceptions of crime and criminals. Socio-economically, the place where crime is likely to occur is important in understanding the factors that contribute to it and the prevention efforts needed to address it (Wells & Wu, 2011). Relatedly, some major concepts in the crime place literature are hotspots and guardianship (see, e.g., Braga *et al*., 2014). The link between hot spots and crime has been a major focus in criminology, especially in crime and place literature. Hotspots are small geographic areas with significant crime concentrations (see, e.g., Eck, *et al*., 2005; Weisburd & Telep, 2014). Therefore, routine activity theory has been one of the major theoretical frameworks used to examine hot spots because it supports the theory's three major factors in predicting deviance and crime as the convergence in time and place of a motivated offender and a suitable target in the absence of a capable guardian. Researchers (e.g., Sampson & Raudenbush, 1999; Brantingham & Brantingham, 1993) have examined the effect of social and physical environments on crime. Specifically, factors such as poverty, residential stability, physical layout/design, and concentration of commercial establishments all contribute to the time and location of deviance and crime. Conversely, neighborhoods that are well-designed and maintained allow for surveillance and have fewer commercial establishments, presenting fewer opportunities for criminal activities. Other research evidence indicates that crime is more likely in cities than rural areas (Glacer & Sacerdote, 1999; Ward *et al*., 2018) due to certain unique conditions, such as where opportunities are significant, as evidenced by low guardianship, and increased likelihood targets, and offenders crossing paths. Of course, even within cities crime will vary by place (Jones & Pridemore, 2019, p. 545). With the city of Houston as the geographical frame of reference, it is important to discuss the socioeconomics and ecological characteristics that shape the likelihood of local crime (Wells *et al*., 2012). Geography is concerned with the intricate interaction between people and their environment with criminal activity. Routine activity theory and social disorganization theory have both been used to examine and analyze "crime geographies" (Andresen, 2006), although not many studies have combined the two theories.

Theoretical Frameworks

Routine activity theory (RAT) (Cohen & Felson, 1979) is focused on the circumstances in which criminal activities occur. For example, we are less likely to see an increase in victimization if routine activities are performed near or within the home where guardianship is likely to be high. Guardianship is a protective factor but deviant lifestyles, target attractiveness, and exposure to possible offenders are risk factors for both criminality and victimization (Spano & Freilich, 2009). Routine activities may impact a target's accessibility and visibility to motivated offenders (Cohen & Felson, 1979). Relatedly, factors such as the number of cocktail lounges, bars, taverns (Roncek & Maier, 1991) gas stations, and grocery stores (Bernasco & Block, 2011) are associated with crime. However, given that the effects of the COVID-19 pandemic are not equally distributed in the population and people are likely to adjust to restrictions in various ways, this study looks specifically at these dynamics in the Houston context in terms of changes in crime trends that are correlated with shifts in signs of disorder and guardianship. Markedly during 2020 law enforcement availability was impacted as persons who tested positive or were exposed to those who tested positive in their agencies also had to quarantine for two weeks like everyone else as there was still no vaccine, et cetera. There was also a marked increase in local gun and ammunition sales that year as the uncertainty of the pandemic and Black Lives Matter protests in the aftermath of the May murder of George Floyd by police generated fears of possible serious impending civil unrest.

While routine activity theory is concerned with opportunities that could predict spatial patterns of crime, social disorganization theory is largely concerned with the impact of various social factors (e.g., family disruption, ethnic diversity, population density, proximity to the city, etc.) on crime. Based on a meta-analysis, Pratt and Cullen (2005) found evidence that social disorganization theory is one theory that had strong empirical predictability across all studies, while routine activity theory had moderate support. We thought it was appropriate to combine both theories to understand how changes in people's daily routines could be linked to crime. Also given Houston's diversity, it is important to note whether the social disorganization theory (in terms of poverty, diverse populations, etc.) increased persons' vulnerability to crime by place. Thus this study utilizes elements of both routine activity theory and social disorganization theory to help explain the association between space, time, and social-ecological dynamics on the interactions of victims and offenders of crime. The physical appearance of a place may also influence deviant and criminal behavior, so by utilizing broadly the social disorganization theoretical framework, we should be able to contextualize crime and provide a more comprehensive overview of the crime problem in Houston.

Social disorganization theory is a social structural theory of crime that helps to explain the variation in crime across neighborhoods. Social disorganization theory postulates that crime is likely to be higher in socially disorganized communities which usually lack factors such as cohesion and informal controls when contrasted with socially organized communities. Much of the early work of this theory came from Park and Burgess (1925), who examined the impact of immigration, industrialization, and urbanization on social organization in certain neighborhoods in Chicago. However, crime was not a part of the discussion until Shaw and McKay's (1942) study, with the guidance of Park and Burgess, that applied the theory to delinquency. Shaw and McKay (1942) found that social problems (e.g., low socio-economic status, residential turnover, unemployment, poverty) and crime were positively correlated (Kubrin, 2009). Pratt and Cullen (2005) also found empirical support for key variables such as family disruption, racial heterogeneity, and poverty, although more recent evidence suggests the tenets of social disorganization theory may not be linear (Kubrin *et al*., 2022). Like routine activity theory, social disorganization emphasizes the importance of "place" given that evidence suggests crime is often clustered in certain areas rather than randomly distributed.

According to Jones and Pridemore (2019), social disorganization or "crime at place research" (p. 546) has relevance for predicting crime at the street level. Weisburd *et al*. (2012) advanced this literature with an examination of social disorganization considering variables such as physical disorder, race of public-school children, and public housing. Empirically socioeconomic status is an important predictor of delinquency (Lander, 1954; Sharkey, 2013). Errol *et al*. (2021) examined decades of social disorganization research in advanced countries, including the United States, and included that crime becomes more common in areas with more broken family structures (e.g., given the divorce rate and number of out-of-wedlock births). While the evidence was significant for urbanization and violent crime, the results for urbanization and property crime were mixed. This was attributed to how urbanization unfolded.

Building on the aforementioned theoretical foundations, we now turn to our methodology, which applies to empirical data from Houston.

Method

Data Collection

Crime cases were collected from Houston Police Department (HPD) which releases monthly National Incident-Based Reporting System (NIBRS) metadata by street/neighborhood (https://www.houstontx.gov/police/cs/Monthly_Crime_Data_ by_Street_and_Police_Beat.htm). The crime cases from HPD follow the NIBRS coding rules and are posted monthly about two weeks later in the month after the crime. The crime report contains the name of the street where the crime took place and is further geocoded into longitude and latitude by geocoding tools from ArcGIS Pro. The 311 events were collected from the Houston 311 website (https://www.houstontx.gov/311/about.html) where the city of Houston government updates the 311 service request data monthly. The released 311 service request data contains information including the date, event category, coordinates of the events, and other details. After getting the coordinates of crime by geocoding and coordinates of the 311 events from raw data, we mapped the selected types of crimes and 311 events within the research area. The number of crimes and 311 events were further counted by census tract using the spatial join tools in ArcGIS Pro.

The application of routine activity theory and social disorganization theory to the Houston context is appropriate given that variables of interest include disruption, residential stability, median income, poverty rate, unemployment, ethnic heterogeneity, and population density as these relate to crime and signs of disorder. A proxy for guardianship is a measure of the availability of a local fire service station and a police station; distance from the city's center and the number of bus stations (for the latter two, offenders and targets are more likely to have interaction but without capable guardians present to intervene). Indeed, the variables utilized largely serve as proxies and correlates for other dynamics that are not easy to quantify regarding those communities where persons experienced the brunt of the negative impact of the pandemic in terms of several persons being forced to quarantine together, loss of jobs, financial challenges, and related stresses such as food and housing insecurity. All of these have the potential to increase the likelihood of victimization in terms of violent conflicts and possibly property offending where lapses in capable guardianship are evident such as with commercial businesses that were forced to close in 2020. Texas' restrictions were short-lived as Governor Greg Abbott declared the state open in May 2020 and local jurisdictions also eased their restrictions accordingly.

To gain a better understanding of crime and disorder in Houston during the most restrictive year (2020), the research questions were:

1. To what extent did different segments of the population (those with family disruption, females, elderly, Blacks, those in more densely populated areas, and those in areas with higher unemployment) experience crime and disorder during the 2020 restrictions?
2. To what extent is guardianship (proximity to fire, police; distance from the city center, and number of bus stations) predictive of crime and signs of disorder during the 2020 restrictions?

3. To what extent are characteristics indicative of less socially organized communities (heterogeneity, instability, poverty) predictive of changes in crime and signs of disorder during the 2020 restrictions?
4. To what extent did COVID-19 policy affect crime and 311 events?

These findings are discussed by comparing changes from 2019 to 2020.

Variables

This study examined four common types of offenses (i.e., aggravated assault, burglary, motor vehicle theft, and robbery) and social disorder as indicated by 311 events (i.e., nuisance on property, dead animal collection, sewer wastewater, and garbage-related events). Li, *et al*. (2020) suggest 311 events may reflect both potential and actual disorder as part of neighborhood distress (neighborhood distress often reflects economic conditions, unemployment, etc.). These data are of crime and disorder within the boundary of the city of Houston, thus we filtered the census tract data accordingly. The number of the census tracts was 337 in 2019 and then 547 in 2020. To ensure a consistent boundary for a more accurate comparison, we combined the 2019 and 2020 census tracts and mainly used the 2020 census tract. Five hundred and fifty in total census tract were finally extracted.

The occurrence of crimes and a number of 311 events can be used to represent the level of disorder in a community, so we used four typical types of crimes robbery, aggravated assault, burglary, and motor vehicle theft, and four types of 311 events which are among the most reported events including nuisance on property, dead animal collection, sewer wastewater and garbage related events (missed garbage pickup, garbage container problem, and missed heavy trash pickup).

Predictors in the regression analysis reflect the perspective of social disorganization theory and routine activity theory (Sampson & Groves, 1989; Sampson *et al*., 1997). According to the literature, disadvantaged socioeconomic status, unstable residential composition, and higher percentages of disrupted families are associated with a potential state of social disorganization or weaker collective efficacy (that is neighborhood guardianship or care of each other) which could reduce the degree of informal control. Informed by the studies of Sampson and Groves (1989), Krivo and Peterson (1996), and Sampson *et al*. (1997), we included ethnic heterogeneity as a measurement for the racial structure of a community because it is associated with the distribution of social disadvantage and strength of neighborhood collective efficacy. Entropy (concerned with the magnitude of diversity or structure of diversity in population) was used to measure ethnic heterogeneity. Variables to measure socioeconomic status, racial heterogeneity, residential instability, and family disruption were derived from the American Community Survey (ACS) five-year estimation in 2020. Socioeconomic status was measured by poverty rate and unemployment rate. Poverty is calculated as the percentage of the population for whom poverty status was determined in the last 12 months. The unemployment rate was calculated by the ratio of people who were unemployed in the labor force to the total number of the population in the labor force. Racial heterogeneity was calculated as a Herfindahl-Hirschman Index based on seven racial groups, including White, Black, or African American, American Indian, Alaska Native, Asian, Native Hawaiian, Other Pacific Islander, other race alone, and two or more races (Boessen *et al.*, 2021). Residential instability was measured as the percentage of individuals who moved their residences from either within the same county, the same state, the country, or abroad. Other sociodemographic variables from ACS were controlled in the model including population density, percentage of elderly, percentage of females, and percentage of Blacks.

Place-based variables from routine activity theory include distance to the city center, distance to the nearest police station, distance to the nearest fire station, and number of bus stations. The distance to police and fire stations are proxy for guardianship such that the closer the location, the more it is assured that there is access to suitable place guardianship. Proximity to the city's center is assumed to be a crime generator as areas where motivated offenders and suitable targets are more likely to interact. The presence of bus stops also increases the opportunities for crime. The location of the police station, fire station, and presence of bus stations were downloaded from the City of Houston Open Data Portal of point-based GIS data.

The distance to the city center was measured by the distance from the centroid of the census tract to the centroid of Harris County based on the GIS digital map of census tract boundaries from the Census Bureau of the United States. The distance to the nearest police station was measured by the distance between the centroid of a census tract to its nearest police station; the distance to the nearest fire station was measured by the distance between the centroid of a census tract to its nearest fire station.

Analysis

The counts of crimes and 311 events are the outcome variables in this study. They were aggregated at the census tract level. Empirical studies usually fit count data models via Negative Binomial Regression (Bernasco & Block, 2011; Hipp *et al.*, 2022; Song *et al.*, 2021; Zhang *et al.*, 2022). Negative Binomial Regression addresses the overdispersion issue which means the variance of the dependent variable is larger than its mean

(Osgood, 2000; Britt *et al.*, 2018). Given our dependent variables are counted events with over-dispersed distribution, we fit our models of crimes and 311 events using Negative Binomial Regression. The models are captured by the following equation:

$$\begin{aligned} E(y_i) = \exp(&\beta_{i0} + \beta_{i1}\, heterogenity + \beta_{i2}\, instability + \beta_{i3}\, disruption + \beta_{i4}\, poverty \\ &+ \beta_{i5}\, unemployment + \beta_{i6}\, center + \beta_{i7}\, police + \beta_{i8}\, fire + \beta_{i9}\, bus \\ &+ \beta_{i10}\, income + \beta_{i11}\, elder + \beta_{i12}\, female + \beta_{i13}\, black + \beta_{i14}\, pop + e_i), \end{aligned}$$

where represents the count of the crime or 311 events which can be aggravated assault, burglary, motor vehicle theft, robbery, nuisance on property, dead animal collection, sewer wastewater, or garbage-related events. is the intercept and is the error term for crime or 311 event. are the coefficients for predictors including ethnic heterogeneity *(heterogeneity)*, residential instability *(instability)*, family disruption *(disruption)*, poverty rate *(poverty)*, unemployment rate *(unemployment)*, distance from city center to the census tract *(center)*, distance to the nearest police station *(police)*, distance to the nearest fire station *(fire)*, number of bus stations *(bus)*, percentage of elder *(elder)*, percentage of females *(female)*, percentage of Blacks *(black)*, and population density *(pop)*. Incidence Rate Ratios (IRRs) are reported in the model results to indicate the change of percentage for the dependent variable by one unit change of predictors. An IRR of a predictor larger than 1 indicates this predictor has a positive relationship with the dependent variable; an IRR of a predictor less than 1 indicates this predictor has a negative relationship with the dependent variable. The multicollinearity issue was examined using the Variance Inflation Factor (VIF). The VIF for each predictor is less than 5 which indicates there is no severe multicollinearity issue.

To better capture the change in crimes and 311 events over time and the effect of the COVID-19 lockdown policy, a time series analysis for the crimes and 311 events was done. The two years' crimes and 311 events data are separated into 10 groups based on months. Each year includes five groups, which are January-February, March-May, June-August, September-November, and December. The main reason for such groups is that March 2020 to May 2020 implemented the most restricted pandemic lockdown policy, and vaccines became available in December 2020. The predictors were extracted from the 2020 ACS five-year estimation. Also, the four types of 311 events were combined into one for a comprehensive analysis.

Findings

For the two-year analysis, the data were effective at identifying predictors of crime in Houston. Specifically, the role of demographic and socio-economic characteristics of

Table 1: *Descriptive Statistics for Variables included in Study Models in 2019 and 2020*

Variables	*N*	*Mean*		*St.D*	*2020*	*2019*	*Min*	*2020*	*Max 2019*	*2020*
		2019	*2020*	*2019*						
Dependent Variables Aggravated assault	550	19.33	24.84	17.91	22.13	0.00		0.00	118	127.00
Burglary	550	24.70	22.28	15.73	15.01	0.00		0.00	86	93.00
Motor vehicle theft	550	19.17	21.09	19.02	17.15	0.00		0.00	125	119.00
Robbery	550	13.86	13.47	12.56	12.03	0.00		0.00	101	96.00
Nuisance on property	550	28.95	26.71	36.32	32.96	0.00		0.00	294	324.00
Dead animal collection	550	11.04	11.18	10.88	10.65	0.00		0.00	70	73.00
Sewer wastewater	550	28.46	37.21	28.31	38.45	0.00		1.00	173	244.00
Garbage related events	550	35.67	37.93	36.28	40.53	0.00		0.00	327	291.00
Predictors Ethnic heterogeneity *(heterogeneity)*	550	0.52		0.15			0.02		0.78	
Residential instability *(instability)*	550	16.88		8.42			2.03		40.61	
Family disruption *(disruption)*	550	7.07		6.18			0.00		40.71	
Poverty rate *(poverty)*	550	20.48		13.45			0.00		79.43	
Unemployment rate *(unemployment)*	550	6.71		5.22			0.00		43.52	
Distance from city center *(center)*	550	15.55		7.12			0.00		33.14	
Distance to the nearest police station *(police)*	550	4.27		2.07			0.22		10.25	
Distance to the nearest fire station *(fire)*	550	1.50		0.68			0.03		4.79	
Number of bus stations *(bus)*	550	13.80		12.40			0.00		123.00	
Median household income *(income)*	550	64.87		45.52		13.29			250.00	
Percentage of elder population *(elder)*	550	11.01		7.32		0.00			53.17	
Percentage of female population *(female)*	550	50.03		5.49		27.76			71.53	
Percentage of Black population *(black)*	550	22.35		24.08		0.00			99.47	
Population density *(pop)*	550	2.89		2.47		0.12			23.89	

neighborhoods, guardianship, family disruption, and residential instability in crime were identified. Table 1 presents the descriptive statistics for 2019 and 2020. In 2019, the mean number of robberies was about 13.86 per census tract, while the number of aggravated assaults was 19.33. For property offenses, burglary had a higher mean rate of 24.70 per census tract than motor vehicle theft at 19.17. Among the four offenses (aggravated assault, burglary, motor vehicle theft, and robbery), burglary had the highest mean rate. When compared to the mean rate in 2020, aggravated assault and motor vehicle theft increased, while burglary and robbery decreased.

Regarding 311 events in 2019, the mean was highest for garbage-related events at 35.67 and lowest for dead animal collection at 11.04, while nuisance on property was 28.95 and sewer wastewater was at 28.46 per census tract. In 2020, the rate for garbage-related events was 37.93 per census tract, the dead animal collection was 11.18, sewer wastewater was 37.21, and nuisance on property was 26.71.

Segments of the Population

To what extent did different segments of the population (those with family disruption, median income, percentage of females, elderly, percent Black population, those in more densely populated areas, those in areas with higher unemployment) experience crime and disorder during the 2020 restrictions? Table 2 presents negative binomial regression models for 2019 for each offense type. The findings suggest some variables are more significant than others. For example, family disruption is significantly positive with aggravated assault, motor vehicle theft, and three 311 events, nuisance on property, dead animal collection and sewer wastewater. Median household income is significantly negative in the crime models except for burglary, and significantly positive in garbage related events model. *The percentage of females,* is significantly negative coefficients in aggravated assault, motor vehicle theft, and robbery, while in the 311 model, percent females is a significantly negative coefficient with garbage-related events. Percent elderly is significantly negative coefficients in aggravated assault and motor vehicle theft. Blacks is significantly positive for all crimes except robbery. Unemployment is not significant in any model.

In the 2020 models (see Table 3), family disruption and females are only significantly positive in robbery. Median household income is significantly negative in four crime models but not significantly in all four 311 models. Percent elderly is significantly negative in aggravated assault, motor vehicle theft, and sewer wastewater. Percent Black is significantly positive in most of the offense types, except robbery and dead animal collection. Percent females is significantly negative in only robbery. Unemployment is not significant in any of the models.

Guardianship and Crime

To what extent is guardianship (proximity to fire, police; distance from the city center, and number of bus stations) predictive of crime and signs of disorder during the 2020 restrictions? The findings are mixed, according to the 2019 models. For example, distance to the city center and distance to the fire station are only significantly negative in some 311 events. There are no significant coefficients in any crime-related model. Distance to the police station is significantly negative with aggravated assault, robbery, and three 311 events: nuisance on property, dead animal collection, and sewer wastewater. On the other hand, the bus station is a positive and significant coefficient in all offense categories (aggravated assault, burglary, motor vehicle theft, robbery, nuisance on property, dead animal collection, sewer wastewater, and garbage-related events).

For the 2020 crime models (see Table 3), bus stations are positively significant in all models of crime and the 311 models. Distance from the city center and distance to the fire station are significantly negative in sewer wastewater. Distance to a police station is significantly negative in aggravated assault, robbery, and sewer wastewater.

Social Disorganization Variables and Crime

To what extent are less socially organized communities (heterogeneity, instability, poverty) predictive of changes in crime and signs of disorder during the 2020 restrictions? In the 2019 models (see Table 2), ethnic heterogeneity had a significant negative relationship with sewer wastewater. Residential instability had a significant positive relationship with burglary but a significant negative relationship with all the social disorder indicators. These results are consistent with social disorganization theory that indicates that crime will be higher when housing is less stable, and persons might not be as ecologically attentive as reflected by the disorder results. The poverty rate is significantly negative in sewer wastewater and garbage-related events.

In the 2020 crime models (see Table 3), the results are also mixed. Regarding ethnic heterogeneity, it is significantly positive in robbery and significantly negative in garbage related. events. Residential instability is significantly negative in all 311 models, and positive in burglary. Poverty is significantly negative with motor vehicle theft and not significant in any of the 311 models.

When comparing 2019 models to 2020 models, several factors exhibit consistent effects in both years, such as residential instability, unemployment rate, and the number of bus stations. Likewise, three distance-based measurements (proximity to fire, police, and distance from the city center) maintain a consistent significance in crime models. Conversely, variables related to the percent Black population, and population density

Table 2: Summary of 2019 Results Based on Negative Binomial Models

Variables	*Aggravated assault*	*Burglary*	*Motor vehicle theft*	*Robbery*	*Nuisance on property*	*Dead animal collection*	*Sewer wastewater*	*Garbage related events*
heterogeneity	0.1695	0.3697	0.2304	0.2681	-0.2213	-0.484	-0.7657**	-0.3818
	(0.2146)	(0.2016)	(0.235)	(0.2566)	(0.3245)	(0.2512)	(0.2723)	(0.3117)
instability	-0.0019	0.0084**	0.0015	-0.0008	-0.0171**	-0.0258**	-0.0154**	-0.0234**
	(0.0028)	(0.0026)	(0.003)	(0.0033)	(0.0048)	(0.0037)	(0.0037)	(0.0043)
disruption	0.0262**	-0.0058	0.0181**	0.0115	0.0388**	0.0383**	0.0402**	0.0172
	(0.0061)	(0.0057)	(0.0068)	(0.0073)	(0.0099)	(0.0074)	(0.0079)	(0.0089)
poverty	0.003	0.0003	-0.0013	0.0052	-0.0078	-0.006	-0.0102**	-0.01**
	(0.003)	(0.0028)	(0.0033)	(0.0036)	(0.0049)	(0.0037)	(0.004)	(0.0045)
unemployment	0.0004	-0.0082	-0.007	-0.0016	0.0132	-0.0069	0.0073	0.0059
	(0.0063)	(0.0059)	(0.0069)	(0.0077)	(0.01)	(0.0076)	(0.0085)	(0.0093)
center	-0.0054	-0.0017	-0.0012	0.002	-0.0255**	-0.0108**	0.0019	0.0057
	(0.004)	(0.0038)	(0.0043)	(0.0049)	(0.006)	(0.0046)	(0.0052)	(0.0057)
police	-0.0429**	-0.0054	-0.0042	-0.0415**	-0.049**	-0.0343**	-0.051**	-0.0226
	(0.0139)	(0.0128)	(0.0148)	(0.0168)	(0.0205)	(0.0158)	(0.0174)	(0.0188)
fire	-0.0358	-0.0211	0.0499	0.0101	-0.2121**	-0.0184	-0.1346**	-0.0328
	(0.0414)	(0.0379)	(0.0455)	(0.0492)	(0.0644)	(0.0466)	(0.0534)	(0.0608)
bus	0.0199**	0.0198**	0.0164**	0.0211**	0.0239**	0.0165**	0.0218**	0.0139**
	(0.0024)	(0.0027)	(0.0027)	(0.0033)	(0.0043)	(0.003)	(0.0036)	(0.0041)
income	-0.0066**	-0.0014	-0.0045**	-0.0073**	0.003	0.0018	0.0017	0.0038**
	(0.0012)	(0.001)	(0.0012)	(0.0014)	(0.0019)	(0.0012)	(0.0014)	(0.0017)
female	-0.0108**	-0.0044	-0.0027	-0.02**	-0.0096	0.0014	-0.0107	-0.0039
	(0.0049)	(0.0046)	(0.0053)	(0.0057)	(0.0081)	(0.0061)	(0.0064)	(0.0075)
elder	-0.0118**	-0.0052	-0.0253**	-0.0059	-0.0138	-0.0023	0.0065	-0.0098
	(0.0042)	(0.0038)	(0.0043)	(0.0049)	(0.0072)	(0.0052)	(0.0057)	(0.0069)
black	0.0059**	0.0071**	-0.0059**	-0.0007	0.0018	-0.0006	-0.0007	0.0015
	(0.0017)	(0.0016)	(0.0018)	(0.002)	(0.0027)	(0.002)	(0.0022)	(0.0024)

Variables	*Aggravated assault*	*Burglary*	*Motor vehicle theft*	*Robbery*	*Nuisance on property*	*Dead animal collection*	*Sewer wastewater*	*Garbage related events*
pop	-0.0296**	-0.0074	-0.0259	0.003	-0.1608**	-0.1337**	-0.1288**	-0.1305**
	(0.0127)	(0.0122)	(0.0136)	(0.0156)	(0.0271)	(0.0221)	(0.0208)	(0.0315)
Constant	3.297**	3.033**	3.1892**	3.5069**	4.4472**	2.8284**	4.1715**	4.3472**
	(0.334)	(0.311)	(0.362)	(0.3914)	(0.5419)	(0.4078)	(0.4334)	(0.5002)
Observations	550	550	550	550	550	550	550	550
AIC	3779	4196	3998	3625	4168	3205	4335	4154
BIC	3847	4265	4067	3693	4235	3272	4403	4219
Log likelihood	-1873	-2082	-1983	-1796	-2068	-1586	-2151	-2061
Pseudo R-squared	0.100	0.034	0.037	0.053	0.058	0.090	0.063	0.029

Note: Incidence rate ratios are reported in the results, and standard errors are provided in parentheses; ** $p<0.05$

Table 3: Summary of 2020 Results Based on Negative Binomial Models

Variables	*Aggravated assault*	*Burglary*	*Motor vehicle theft*	*Robbery*	*Nuisance on property*	*Dead animal collection*	*Sewer wastewater*	*Garbage related events*
heterogeneity	0.1668	0.3341	0.2692	0.6256**	-0.3224	-0.7436	-0.6132	-0.7357**
	(0.2308)	(0.2322)	(0.258)	(0.2695)	(0.2942)	(0.4723)	(0.3577)	(0.3377)
instability	-0.0026	0.0149**	0.0058	0.0008	-0.0219**	-0.0312**	-0.0262**	-0.0217**
	(0.0027)	(0.0029)	(0.0031)	(0.0033)	(0.0037)	(0.0059)	(0.0048)	(0.0041)
disruption	0.0065	0.0058	0.0124	0.017**	0.0023	0.0047	0.0055	-0.0093
	(0.006)	(0.0059)	(0.0067)	(0.0068)	(0.0073)	(0.0124)	(0.0092)	(0.0086)
poverty	0.0027	-0.0048	-0.008**	0.0011	-0.0008	-0.0088	-0.008	-0.0027
	(0.0033)	(0.0032)	(0.0037)	(0.0038)	(0.0041)	(0.007)	(0.0054)	(0.0049)
unemployment	-0.0028	-0.0038	-0.0108	0.0011	-0.0016	-0.0093	0.0032	0.0122
	(0.0069)	(0.0068)	(0.0078)	(0.008)	(0.0083)	(0.0134)	(0.0107)	(0.0105)
center	-0.0002	-0.0063	-0.0017	0.0032	-0.0035	0.0079	-0.0168**	0.0073
	(0.0043)	(0.0044)	(0.0049)	(0.0051)	(0.0053)	(0.0085)	(0.0069)	(0.0062)
police	-0.0324**	-0.0199	0.003	-0.0407**	-0.03	-0.0358	-0.0696**	-0.0362
	(0.0147)	(0.0145)	(0.0162)	(0.0174)	(0.0176)	(0.0284)	(0.0235)	(0.021)
fire	0.0161	0.0083	0.0337	-0.0191	0.0114	-0.0906	**-0.1879****	-0.1286
	(0.0441)	(0.0438)	(0.0504)	(0.0518)	(0.0534)	(0.0893)	(0.0739)	(0.0658)
bus	0.0217**	0.017**	0.017**	0.0219**	0.0219**	0.0225**	0.0331**	0.0226**
	(0.0028)	(0.003)	(0.0031)	(0.0035)	(0.0037)	(0.0067)	(0.0052)	(0.0046)
income	-0.011**	-0.0051**	-0.0084**	-0.0087**	-0.0018	0.0003	-0.0026	-0.0013
	(0.0011)	(0.001)	(0.0011)	(0.0013)	(0.0012)	(0.0023)	(0.0018)	(0.0015)
female	-0.0065	-0.0057	-0.0043	-0.0236**	0.0032	0.0067	-0.0101	0.0011
	(0.0056)	(0.0055)	(0.0061)	(0.0064)	(0.0072)	(0.0119)	(0.0091)	(0.0084)
elder	-0.0117**	-0.0047	-0.0233**	-0.0102	0.0065	-0.0066	**-0.0165****	0.0064
	(0.0046)	(0.0046)	(0.005)	(0.0054)	(0.0061)	(0.0102)	(0.0079)	(0.0076)

Variables	*Aggravated assault*	*Burglary*	*Motor vehicle theft*	*Robbery*	*Nuisance on property*	*Dead animal collection*	*Sewer wastewater*	*Garbage related events*
black	0.0093**	0.0035**	-0.0039**	0.0012	0.0046**	0.0032	0.0067**	0.005**
	(0.0015)	(0.0015)	(0.0017)	(0.0018)	(0.0018)	(0.003)	(0.0024)	(0.0023)
pop	**-0.0281****	-0.0255	**-0.0354****	-0.0025	-0.1483**	-0.2726**	-0.1836**	-0.1978**
	(0.014)	(0.0145)	(0.0148)	(0.0167)	(0.0211)	(0.0372)	(0.0272)	(0.0241)
Constant	3.7126**	3.2844**	3.8152**	3.6507**	2.8507**	4.8078**	5.4973**	4.5252**
	(0.3565)	-0.3527	(0.3895)	(0.411)	(0.4386)	(0.7409)	(0.584)	(0.5233)
Observations	550	550	550	550	550	550	550	550
AIC	4256	4318	4309	3782	4461	3568	4869	4814
BIC	4324	4387	4378	3851	4530	3637	4938	4883
Log likelihood	-2111	-2142	-2138	-1875	-2214	-1768	-2418	-2391
Pseudo R-squared	0.091	0.033	0.033	0.059	0.052	0.069	0.047	0.031

Note: Incidence rate ratios are reported in the results, and standard errors are provided in parentheses; ** $p<0.05$

consistently exhibit significance in 311 event models for both years. However, for all other variables, their significance varies across different models in the two years.

Time Series Analysis of the Crimes and 311 Events

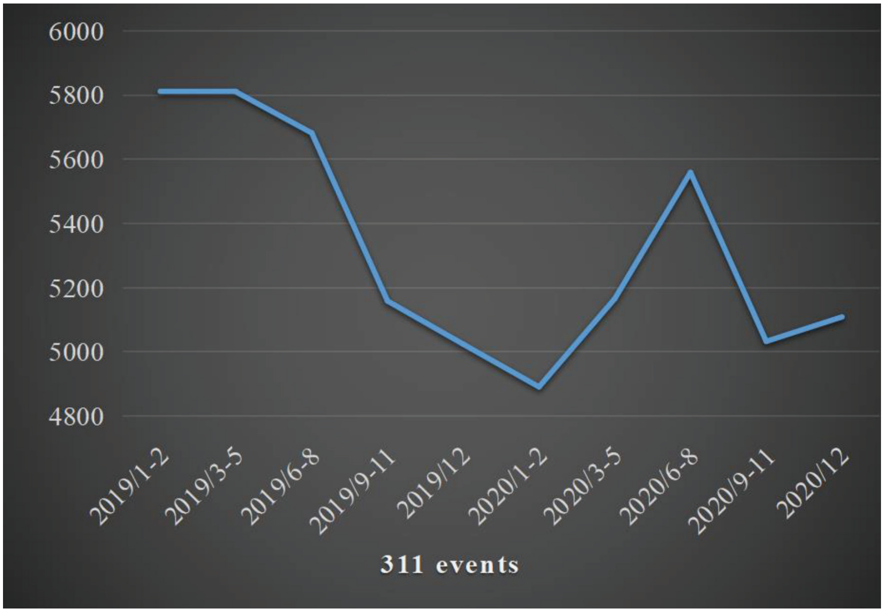

Figure 1: Monthly 311 events count change over time.

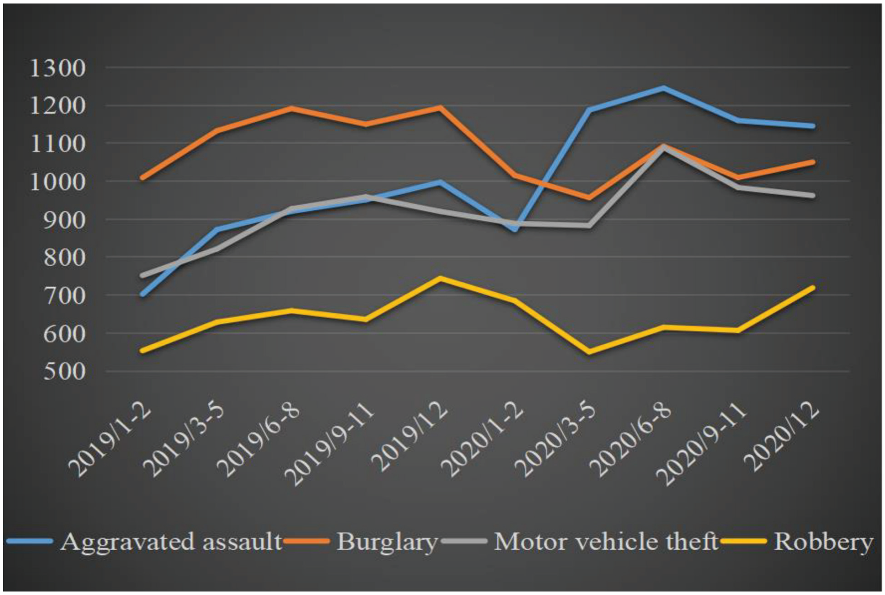

Figure 2: Monthly average crimes count change over time.

When comparing the four types of crimes and 311 events, it becomes evident that burglary, motor vehicle theft, and robbery share a similar trend. The lowest monthly crime count for the three types of crimes is from March to May 2020, which the lockdown policy of Houston may impact. On the other hand, when considering aggravated assault and 311 events, the lowest monthly count was observed in January and February 2020, followed by an upward trend, peaking between June and August 2020. Notably, aggravated assaults have been steadily increasing since 2019, while 311 events steadily declined from the beginning of that year.

Figure 2. Coefficients change of Negative Binomial Models for Crimes and 311 events Over Time.

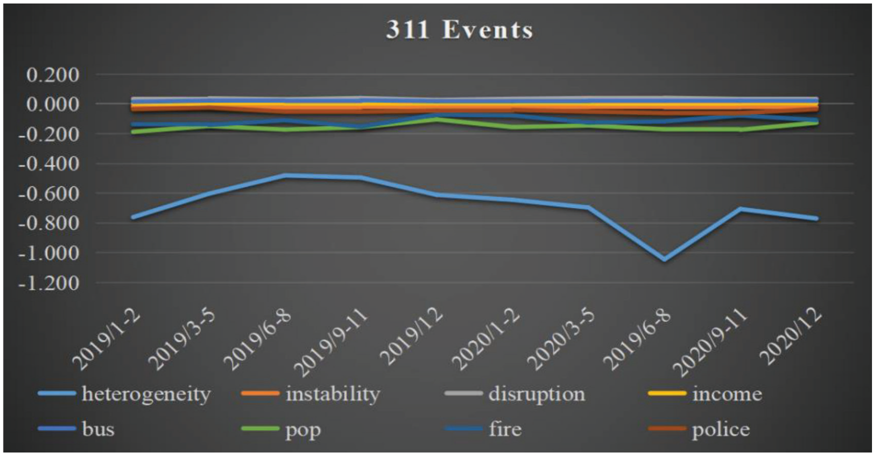

Figure 3: Coefficients change of Negative Binomial Models for 311 events Over Time.

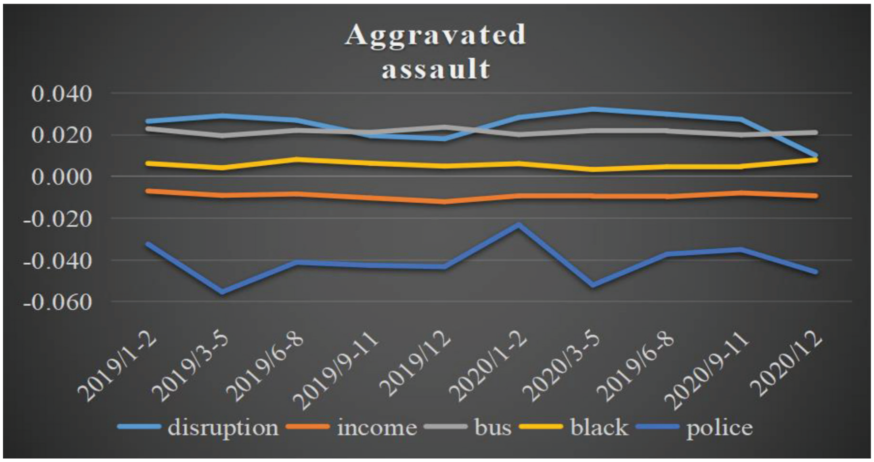

Figure 4: Coefficients change of Negative Binomial Models for Aggravated Assault Over Time.

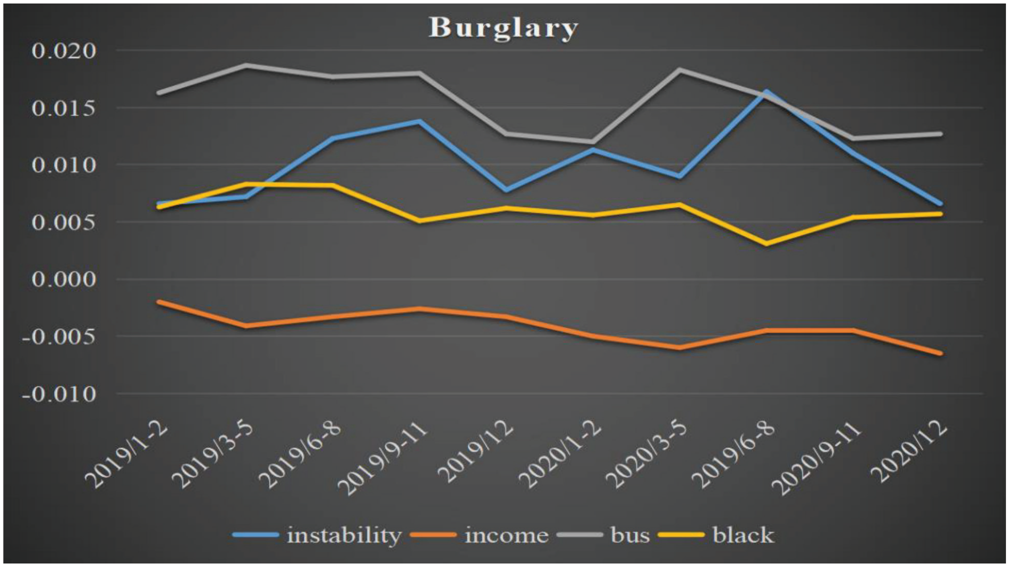

Figure 5: Coefficients change of Negative Binomial Models for Burglary Over Time.

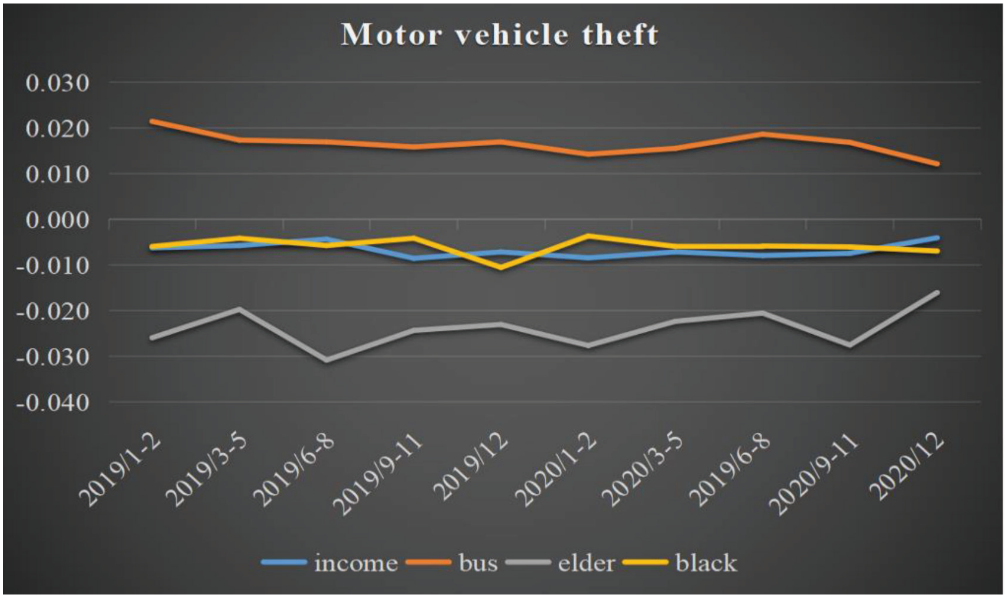

Figure 6: Coefficients change of Negative Binomial Models for Motor Vehicle Theft Over Time.

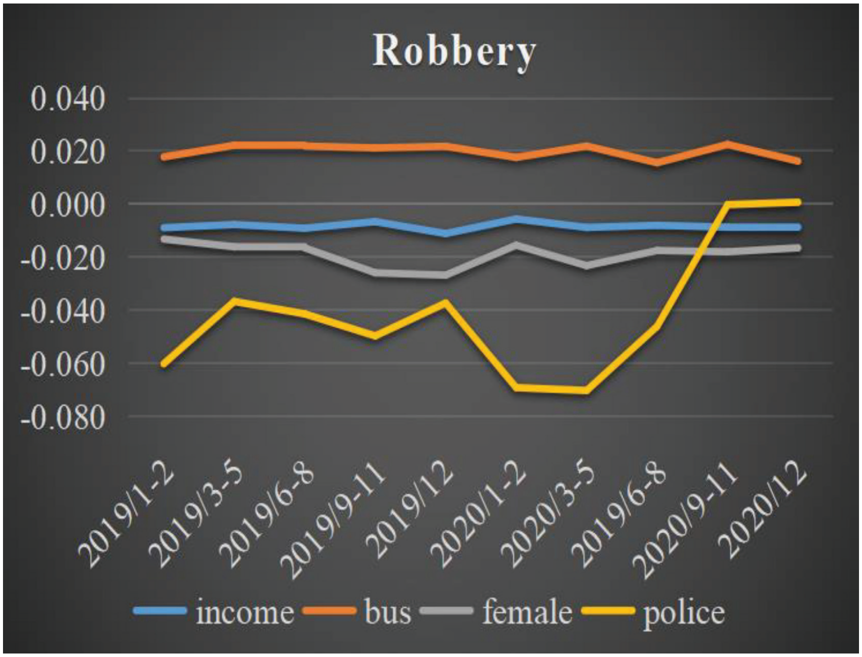

Figure 7: Coefficients change of Negative Binomial Models for Robbery Over Time.

We applied the negative binomial model to each stage of both crimes and 311 events, with the model results presented in Tables 4 through 8. These tables reveal that significant variables exhibit temporal changes. We have visualized the coefficients in line charts to facilitate a more intuitive comparison of these variables, as depicted in Figure 2.

For burglary, the four significant factors are *residential instability, median income, bus stations, and percent Black population*. The coefficients of variable *instability and bus* have an apparent fluctuation during 2020/March-May. The coefficient of *residential instability* has a decreasing trend, while the coefficient of *bus stations* has an increasing trend. For robbery, there are four significant variables, which are *median income, bus stations, percentage of females,* and *proximity to a police station*. The first three variables do not change much, and the coefficient of variable *proximity to a police station* has a significant decrease during 2020/March-May. For motor vehicle theft, *median income, bus stations, percentage of elderly,* and *percentage of Black population* are the four significant variables. No obvious change is found during 2020/March-May. For aggravated assault, there are five significant variables, which are *family disruption, median income, bus stations, percent Black population*, and *proximity to a police station*, and the variable coefficient *proximity to a police station* has a significant decrease

Table 4: Summary of Aggravated assault Results Based on Negative Binomial Models

	2019					*2020*				
	01-02	*03-05*	*06-08*	*09-11*	*12*	*01-02*	*03-05*	*06-08*	*09-11*	*12*
intercept	0.807	2.011**	1.901**	2.275**	1.211**	1.320**	1.722**	1.865**	1.759**	0.415
	(0.4833)	(0.4166)	(0.4097)	(0.4326)	(0.5138)	(0.4583)	(0.3918)	(0.4247)	(0.3864)	(0.4869)
heterogeneity	0.341	0.066	0.320	0.247	0.020	0.373	0.119	0.364	0.246	0.309
	(0.3046)	(0.2613)	(0.2605)	(0.2753)	(0.3191)	(0.2912)	(0.2475)	(0.2711)	(0.2406)	(0.3066)
instability	-0.005	0.001	0.000	0.004	0.004	-0.002	0.003	0.003	0.004	-0.002
	(0.0042)	(0.0035)	(0.0035)	(0.0035)	(0.0042)	(0.0039)	(0.0031)	(0.0035)	(0.0031)	(0.0042)
disruption	0.026**	0.029**	0.027**	0.020**	0.018**	0.028**	0.032**	0.030**	0.027**	0.010
	(0.0084)	(0.0074)	(0.0075)	(0.0077)	(0.009)	(0.0084)	(0.007)	(0.0077)	(0.0069)	(0.0085)
poverty	0.005	0.003	-0.001	0.000	-0.003	-0.002	-0.001	0.001	0.003	-0.001
	(0.0043)	(0.0037)	(0.0037)	(0.0038)	(0.0046)	(0.0041)	(0.0035)	(0.0038)	(0.0034)	(0.0042)
unemployment	-0.001	0.002	-0.001	0.001	-0.006	-0.006	0.001	-0.005	-0.007	0.004
	(0.0085)	(0.0074)	(0.0074)	(0.0076)	(0.009)	(0.0083)	(0.0071)	(0.0078)	(0.0069)	(0.008)
income	-0.007**	-0.009**	-0.008**	-0.010**	-0.012**	-0.009**	-0.010**	-0.010**	-0.008**	-0.009**
	(0.0018)	(0.0016)	(0.0015)	(0.0016)	(0.0022)	(0.0018)	(0.0014)	(0.0015)	(0.0014)	(0.0019)
bus	0.023**	0.020**	0.022**	0.021**	0.024**	0.020**	0.022**	0.022**	0.020**	0.021**
	(0.0032)	(0.0027)	(0.0028)	(0.0031)	(0.0032)	(0.0031)	(0.0028)	(0.003)	(0.0028)	(0.0031)
elder	-0.011	-0.006	-0.014**	-0.007	-0.018**	-0.011	-0.011**	-0.007	-0.009	-0.001
	(0.0063)	(0.0053)	(0.0055)	(0.0056)	(0.0072)	(0.0061)	(0.0051)	(0.0055)	(0.0051)	(0.0062)
black	0.006**	0.004**	0.008**	0.006**	0.005**	0.006**	0.003	0.005**	0.005**	0.008**
	(0.0023)	(0.002)	(0.002)	(0.0021)	(0.0024)	(0.0022)	(0.0019)	(0.002)	(0.0019)	(0.0023)
pop	0.003	-0.040**	-0.027	-0.017	-0.027	0.006	-0.008	-0.030	-0.024	-0.016
	(0.0185)	(0.0169)	(0.0156)	(0.0162)	(0.0198)	(0.0176)	(0.015)	(0.0161)	(0.0149)	(0.0195)

	2019					2020				
	01-02	*03-05*	*06-08*	*09-11*	*12*	*01-02*	*03-05*	*06-08*	*09-11*	*12*
female	-0.007	-0.011	-0.011	**-0.014****	-0.006	-0.007	-0.002	-0.007	-0.007	-0.001
	(0.007)	(0.006)	(0.006)	(0.0062)	(0.0072)	(0.0066)	(0.0057)	(0.0063)	(0.0057)	(0.007)
center	-0.007	-0.007	-0.006	-0.004	-0.005	-0.008	-0.004	0.000	-0.001	0.004
	(0.0056)	(0.0049)	(0.0049)	(0.0051)	(0.0061)	(0.0054)	(0.0047)	(0.005)	(0.0046)	(0.0058)
fire	-0.028	-0.014	-0.027	-0.053	0.009	-0.070	0.011	-0.011	0.008	0.094
	(0.0594)	(0.0508)	(0.0498)	(0.0531)	(0.0627)	(0.0567)	(0.0467)	(0.0512)	(0.0469)	(0.0587)
police	-0.032	**-0.055****	-0.041	**-0.043****	**-0.043****	-0.023	**-0.052****	**-0.037****	**-0.035****	**-0.046****
	(0.02)	(0.0172)	(0.017)	(0.0178)	(0.0216)	(0.0192)	(0.0161)	(0.0174)	(0.0159)	(0.0202)
alpha	**0.277****	**0.273****	**0.283****	**0.333****	**0.217****	**0.297****	**0.276****	**0.364****	**0.274****	**0.217****
	(0.0446)	(0.0343)	(0.0345)	(0.0373)	(0.0513)	(0.0429)	(0.0302)	(0.0368)	(0.0302)	(0.0444)
Observations	550	550	550	550	550	550	550	550	550	550
AIC	2067.347	2586.288	2633.252	2713.381	1798.849	2276.389	2871.080	2968.49	2879.123	1908.175
BIC	2136.305	2655.247	2702.211	2782.340	1867.808	2345.347	2940.039	3037.447	2948.082	1977.134
Log likelihood	-1017.7	-1277.1	-1300.6	-1340.7	-883.42	-1122.2	-1419.5	-1468.2	-1423.6	-938.09
Pseudo R-squared	0.123	0.125	0.126	0.108	0.121	0.110	0.120	0.106	0.109	0.118

Note: Incidence rate ratios are reported in the results, and standard errors are provided in parentheses; ** p<0.05

Table 5: Summary of Burglary Results Based on Negative Binomial Models

	2019					*2020*				
	01-02	*03-05*	*06-08*	*09-11*	*12*	*01-02*	*03-05*	*06-08*	*09-11*	*12*
intercept	1.210**	1.799**	1.646**	1.504**	1.279**	1.626**	1.909**	2.090**	1.638**	0.487
	(0.4624)	(0.3926)	(0.3805)	(0.389)	(0.5224)	(0.4435)	(0.4012)	(0.4334)	(0.4208)	(0.5318)
heterogeneity	0.366	0.450	0.428	0.416	-0.105	0.500	0.150	0.246	0.586**	0.139
	(0.301)	(0.2577)	(0.2464)	(0.2477)	(0.3317)	(0.283)	(0.2597)	(0.2833)	(0.2668)	(0.3373)
instability	0.007	0.007**	0.012**	0.014**	0.008	0.011**	0.009**	0.016**	0.011**	0.007
	(0.004)	(0.0033)	(0.0032)	(0.0032)	(0.0044)	(0.0037)	(0.0034)	(0.0037)	(0.0035)	(0.0046)
disruption	-0.006	-0.006	-0.012	0.000	-0.007	-0.013	-0.017**	-0.009	0.000	-0.003
	(0.0088)	(0.0072)	(0.0071)	(0.0069)	(0.0094)	(0.008)	(0.0074)	(0.0082)	(0.0076)	(0.01)
poverty	-0.001	-0.004	0.001	-0.001	-0.001	0.001	-0.001	0.001	-0.003	-0.009
	(0.0042)	(0.0036)	(0.0035)	(0.0035)	(0.0046)	(0.0039)	(0.0036)	(0.0039)	(0.0037)	(0.0049)
unemployment	0.003	-0.006	-0.012	-0.007	-0.016	0.004	-0.007	0.003	-0.008	-0.001
	(0.0086)	(0.0072)	(0.0072)	(0.0074)	(0.0102)	(0.0083)	(0.0074)	(0.0085)	(0.0078)	(0.0099)
income	-0.002	-0.004**	-0.003**	-0.003**	-0.003**	-0.005**	-0.006**	-0.005**	-0.005**	-0.007**
	(0.0014)	(0.0012)	(0.0012)	(0.0012)	(0.0016)	(0.0014)	(0.0013)	(0.0013)	(0.0013)	(0.0018)
bus	**0.016****	**0.019****	**0.018****	**0.018****	**0.013****	**0.012****	**0.018****	**0.016****	**0.012****	0.013**
	(0.0037)	(0.0032)	(0.0031)	(0.0031)	(0.0039)	(0.0033)	(0.0031)	(0.0035)	(0.0033)	(0.0039)
elder	0.003	-0.008	-0.002	-0.003	-0.009	0.001	-0.007	-0.006	-0.009	-0.014**
	(0.0058)	(0.005)	(0.0047)	(0.0049)	(0.0066)	(0.0056)	(0.0052)	(0.0056)	(0.0053)	(0.0072)
black	**0.006****	**0.008****	**0.008****	**0.005****	**0.006****	0.006**	0.007**	0.003	0.005**	0.006**
	(0.0024)	(0.002)	(0.002)	(0.0019)	(0.0026)	(0.0022)	(0.002)	(0.0022)	(0.0021)	(0.0027)
pop	-0.010	-0.002	-0.010	-0.011	0.003	-0.036**	-0.028	-0.033	-0.025	-0.009
	(0.0193)	(0.0153)	(0.0154)	(0.0153)	(0.0207)	(0.0181)	(0.0162)	(0.0178)	(0.0168)	(0.0212)

	2019					*2020*				
	01-02	*03-05*	*06-08*	*09-11*	*12*	*01-02*	*03-05*	*06-08*	*09-11*	*12*
female	-0.006	-0.006	0.000	0.000	-0.003	-0.008	-0.003	-0.007	0.001	0.009
	(0.0068)	(0.0058)	(0.0056)	(0.0058)	(0.0077)	(0.0064)	(0.0059)	(0.0064)	(0.0062)	(0.0079)
center	-0.002	0.003	-0.003	-0.010**	-0.013**	-0.007	0.003	-0.009	-0.009	0.001
	(0.0058)	(0.005)	(0.0048)	(0.0048)	(0.0065)	(0.0054)	(0.005)	(0.0054)	(0.0052)	(0.0067)
fire	0.010	0.003	-0.039	0.003	-0.031	0.003	0.029	-0.035	0.027	0.031
	(0.0556)	(0.0487)	(0.0474)	(0.047)	(0.0638)	(0.0542)	(0.0486)	(0.0533)	(0.0513)	(0.0649)
police	-0.016	-0.007	-0.012	-0.017	0.001	-0.006	-0.006	0.000	-0.039**	-0.019
	(0.0195)	(0.0162)	(0.016)	(0.016)	(0.0216)	(0.018)	(0.0167)	(0.018)	(0.0173)	(0.0222)
alpha	**0.411****	**0.324****	**0.306****	**0.304****	**0.399****	**0.334****	**0.309****	**0.424****	**0.364****	**0.379****
	(0.0455)	(0.0324)	(0.0301)	(0.03)	(0.0587)	(0.0402)	(0.0323)	(0.0381)	(0.0352)	(0.0587)
Observations	550	550	550	550	550	550	550	550	550	550
AIC	2582.685	3010.563	3044.308	3007.760	2119.427	2547.462	2834.515	3022.776	2920.528	1990.638
BIC	2651.643	3079.521	3113.267	3076.718	2188.386	2616.421	2903.474	3091.735	2989.486	2059.596
Log likelihood	-1275.3	-1489.3	-1506.2	-1487.9	-1043.7	-1257.7	-1401.3	-1495.4	-1444.3	-979.32
Pseudo R-squared	0.026	0.042	0.043	0.042	0.024	0.036	0.043	0.035	0.037	0.034

Note: Incidence rate ratios are reported in the results, and standard errors are provided in parentheses; ** $p<0.05$

Table 6: Summary of Motor Vehicle Theft Results Based on Negative Binomial Models

	2019					2020				
	01-02	*03-05*	*06-08*	*09-11*	*12*	*01-02*	*03-05*	*06-08*	*09-11*	*12*
intercept	1.237**	1.849**	1.655**	2.301**	0.473	2.515**	1.620**	2.615**	1.780**	-0.139
	(0.5243)	(0.4822)	(0.4462)	(0.4377)	(0.5797)	(0.5277)	(0.4452)	(0.4533)	(0.4645)	(0.5743)
heterogeneity	0.129	0.206	0.605	0.160	0.539	-0.042	0.230	0.163	0.456	0.991**
	(0.3415)	(0.3069)	(0.2872)	(0.2875)	(0.3667)	(0.3278)	(0.2798)	(0.2929)	(0.3013)	(0.3647)
instability	0.002	0.006	0.001	0.002	0.017**	0.004	0.012**	0.005	0.006	0.007
	(0.0042)	(0.0039)	(0.0037)	(0.0037)	(0.0046)	(0.0044)	(0.0036)	(0.0039)	(0.0039)	(0.0046)
disruption	0.008	0.017	0.023**	0.011	0.032**	0.004	0.027**	0.014	-0.001	0.028**
	(0.0096)	(0.009)	(0.0083)	(0.0084)	(0.0106)	(0.01)	(0.0082)	(0.0087)	(0.0088)	(0.0104)
poverty	0.000	-0.003	-0.002	-0.005	-0.008	-0.006	-0.008	-0.007	-0.007	0.000
	(0.0047)	(0.0044)	(0.004)	(0.004)	(0.0051)	(0.0048)	(0.004)	(0.0042)	(0.0042)	(0.0051)
unemployment	-0.010	-0.009	-0.015	-0.008	-0.004	-0.013	-0.011	-0.015	-0.008	-0.010
	(0.0098)	(0.009)	(0.0084)	(0.0084)	(0.0106)	(0.0097)	(0.0083)	(0.0091)	(0.0089)	(0.0105)
income	-0.006**	-0.006**	-0.004**	-0.009**	-0.007**	-0.008**	-0.007**	-0.008**	-0.007**	-0.004**
	(0.0016)	(0.0015)	(0.0014)	(0.0015)	(0.002)	(0.0017)	(0.0014)	(0.0015)	(0.0015)	(0.0019)
bus	0.022**	0.017**	0.017**	0.016**	0.017**	0.014**	0.016**	0.019**	0.017**	0.012**
	(0.0039)	(0.0034)	(0.0032)	(0.0032)	(0.0037)	(0.0039)	(0.0033)	(0.0034)	(0.0034)	(0.0039)
elder	-0.026**	-0.020**	-0.031**	-0.024**	-0.023**	-0.028**	-0.022**	-0.021**	-0.028**	-0.016**
	(0.0068)	(0.0059)	(0.0058)	(0.0057)	(0.0079)	(0.0067)	(0.0057)	(0.0059)	(0.006)	(0.0074)
black	-0.006**	-0.004	-0.006**	-0.004	-0.011**	-0.004	-0.006**	-0.006**	-0.006**	-0.007**
	(0.0026)	(0.0024)	(0.0023)	(0.0022)	(0.0029)	(0.0026)	(0.0022)	(0.0023)	(0.0024)	(0.0028)
pop	-0.022	-0.034	-0.016	-0.018	-0.055**	-0.046**	-0.019	-0.037**	-0.042**	-0.005
	(0.0199)	(0.0183)	(0.0165)	(0.0173)	(0.0231)	(0.02)	(0.0168)	(0.0177)	(0.0182)	(0.0202)

	2019					*2020*				
	01-02	*03-05*	*06-08*	*09-11*	*12*	*01-02*	*03-05*	*06-08*	*09-11*	*12*
female	0.002	-0.004	-0.002	-0.002	-0.004	-0.008	-0.001	-0.009	0.010	0.005
	(0.0075)	(0.0069)	(0.0065)	(0.0065)	(0.0084)	(0.0077)	(0.0064)	(0.0066)	(0.0066)	(0.0084)
center	0.002	-0.002	-0.001	-0.003	-0.006	-0.002	-0.002	0.003	-0.001	-0.011
	(0.0064)	(0.0057)	(0.0053)	(0.0053)	(0.0066)	(0.0061)	(0.0054)	(0.0056)	(0.0057)	(0.0068)
fire	0.004	0.045	0.101	-0.004	0.066	0.027	0.062	0.008	0.013	-0.001
	(0.0637)	(0.0598)	(0.0545)	(0.0547)	(0.0679)	(0.0647)	(0.0534)	(0.0569)	(0.0582)	(0.0685)
police	0.001	-0.018	-0.042**	0.009	0.011	-0.014	-0.004	0.008	0.000	-0.011
	(0.0213)	(0.0194)	(0.018)	(0.018)	(0.0229)	(0.0208)	(0.018)	(0.0183)	(0.0192)	(0.0235)
alpha	0.467**	0.490**	0.414**	0.416**	0.374**	0.522**	0.384**	0.485**	0.484**	0.393**
	(0.0549)	(0.0468)	(0.0404)	(0.0395)	(0.0645)	(0.0546)	(0.0384)	(0.0418)	(0.043)	(0.0645)
Observations	550	550	550	550	550	550	550	550	550	550
AIC	2303.442	2766.679	2840.372	2878.164	1851.355	2472.141	2785.821	3030.051	2932.958	1913.834
BIC	2372.400	2835.638	2909.331	2947.122	1920.314	2541.09	2854.780	3099.010	3001.917	1982.793
Log likelihood	-1135.7	-1367.3	-1404.2	-1423.1	-909.68	-1220.1	-1376.9	-1499.0	-1450.5	-940.92
Pseudo R-squared	0.040	0.037	0.048	0.044	0.057	0.034	0.047	0.038	0.037	0.041

Note: Incidence rate ratios are reported in the results, and standard errors are provided in parentheses; ** $p<0.05$

Table 7: Summary of Robbery Results based on Negative Binomial Models

	2019					2020				
	01-02	*03-05*	*06-08*	*09-11*	*12*	*01-02*	*03-05*	*06-08*	*09-11*	*12*
Intercept	1.514**	2.006**	1.900**	2.125**	1.625**	1.295**	1.906**	1.845**	1.829**	1.403**
	(0.5605)	(0.4786)	(0.493)	(0.5207)	(0.644)	(0.563)	(0.5181)	(0.494)	(0.4997)	(0.6573)
heterogeneity	0.278	0.315	0.591	0.511	0.181	0.860**	0.401	0.744**	0.760**	0.355
	(0.3591)	(0.3084)	(0.3211)	(0.347)	(0.4042)	(0.3756)	(0.3284)	(0.3158)	(0.3205)	(0.4157)
instability	0.006	-0.005	0.002	0.003	-0.002	-0.002	0.005	0.003	0.001	-0.004
	(0.0045)	(0.0041)	(0.0042)	(0.0043)	(0.0053)	(0.0048)	(0.0042)	(0.004)	(0.0042)	(0.0052)
disruption	0.004	0.014	0.011	0.014	0.009	0.013	0.012	0.011	0.007	0.003
	(0.0098)	(0.0088)	(0.0092)	(0.0096)	(0.0116)	(0.0106)	(0.0093)	(0.0089)	(0.0091)	(0.0117)
poverty	0.008	0.004	0.005	0.009	0.001	0.003	0.005	0.006	0.001	0.002
	(0.0049)	(0.0043)	(0.0045)	(0.0047)	(0.0057)	(0.0051)	(0.0046)	(0.0043)	(0.0044)	(0.0057)
unemployment	-0.012	-0.004	-0.005	-0.014	0.001	0.003	0.001	0.004	0.001	-0.008
	(0.01)	(0.0091)	(0.0093)	(0.0101)	(0.0118)	(0.0106)	(0.0097)	(0.0089)	(0.0092)	(0.0118)
income	**-0.009****	**-0.008****	**-0.009****	**-0.007****	**-0.011****	**-0.006****	**-0.009****	**-0.008****	**-0.009****	**-0.009****
	(0.0021)	(0.0017)	(0.0018)	(0.0018)	(0.0025)	(0.0019)	(0.0019)	(0.0017)	(0.0018)	(0.0024)
bus	**0.018****	**0.022****	**0.022****	**0.021****	**0.022****	**0.018****	**0.022****	**0.016****	**0.023****	0.016**
	(0.0042)	(0.0037)	(0.0039)	(0.0041)	(0.0045)	(0.0041)	(0.0039)	(0.0035)	(0.004)	(0.0045)
elder	-0.011	-0.009	-0.005	-0.005	0.004	-0.015**	-0.006	-0.006	-0.014**	-0.021**
	(0.0073)	(0.0062)	(0.0064)	(0.0068)	(0.0082)	(0.0075)	(0.0067)	(0.0064)	(0.0065)	(0.0089)
black	0.002	0.001	0.001	0.002	-0.005	0.001	0.001	-0.001	0.000	0.000
	(0.0026)	(0.0024)	(0.0025)	(0.0026)	(0.0032)	(0.0028)	(0.0025)	(0.0024)	(0.0025)	(0.0031)
pop	-0.001	0.018	0.025	-0.017	0.003	0.017	0.003	-0.011	0.006	0.005
	(0.0205)	(0.0186)	(0.0191)	(0.0206)	(0.0238)	(0.022)	(0.0193)	(0.0187)	(0.0192)	(0.0245)

	2019					*2020*				
	01-02	*03-05*	*06-08*	*09-11*	*12*	*01-02*	*03-05*	*06-08*	*09-11*	*12*
female	-0.013	-0.016**	-0.017**	-0.026**	-0.027**	-0.016	-0.023**	-0.018**	-0.018**	-0.017
	(0.008)	(0.007)	(0.0072)	(0.0078)	(0.0093)	(0.0082)	(0.0075)	(0.0071)	(0.0072)	(0.0096)
center	0.005	-0.004	-0.004	0.000	0.019**	0.000	0.009	0.002	0.002	0.010
	(0.0068)	(0.006)	(0.0061)	(0.0064)	(0.0079)	(0.0071)	(0.0063)	(0.0059)	(0.0061)	(0.0079)
fire	-0.058	-0.041	-0.050	0.034	-0.002	0.024	0.020	-0.053	-0.042	-0.138
	(0.069)	(0.0594)	(0.0612)	(0.0658)	(0.0776)	(0.0709)	(0.0628)	(0.0602)	(0.0616)	(0.0786)
police	**-0.060****	-0.037	-0.041**	-0.050**	-0.037	-0.069**	-0.070**	-0.046**	0.000	0.001
	(0.0236)	(0.0204)	(0.0209)	(0.0225)	(0.027)	(0.0242)	(0.0218)	(0.0205)	(0.0213)	(0.0271)
alpha	**0.441****	**0.419****	**0.465****	**0.558****	**0.492****	**0.596****	**0.464****	**0.419****	**0.467****	**0.502****
	(0.0649)	(0.0478)	(0.0506)	(0.0574)	(0.0862)	(0.0694)	(0.0549)	(0.048)	(0.0514)	(0.0885)
Observations	550	550	550	550	550	550	550	550	550	550
AIC	1994.404	2438.230	2485.549	2486.009	1688.420	2203.483	2315.266	2429.834	2435.129	1681.722
BIC	2063.363	2507.189	2554.507	2554.968	1757.379	2272.442	2384.225	2498.793	2504.087	1750.68
Log likelihood	-981.20	-1203.1	-1226.8	-1227.0	-828.21	-1085.7	-1141.6	-1198.9	-1201.6	-824.86
Pseudo R-squared	0.066	0.071	0.071	0.060	0.060	0.056	0.076	0.066	0.060	0.048

Note: Incidence rate ratios are reported in the results, and standard errors are provided in parentheses; ** $p<0.05$

Table 8: Summary of 311events Results Based on Negative Binomial Models

	2019					*2020*				
	01-02	*03-05*	*06-08*	*09-11*	*12*	*01-02*	*03-05*	*06-08*	*09-11*	*12*
Intercept	**4.109****	**4.195****	**4.330****	3.806**	2.677**	3.474**	4.043**	4.468**	3.778**	2.730**
	(0.4546)	(0.4473)	(0.4664)	(0.433)	(0.4407)	(0.4343)	(0.4602)	(0.4523)	(0.4353)	(0.4355)
heterogeneity	**-0.761****	**-0.604****	-0.481	-0.495	**-0.612****	**-0.645****	**-0.697****	**-1.046****	**-0.707****	**-0.771****
	(0.2852)	(0.2779)	(0.2935)	(0.2709)	(0.2735)	(0.28)	(0.2907)	(0.2766)	(0.272)	(0.2697)
instability	**-0.018****	**-0.023****	**-0.023****	**-0.019****	**-0.023****	**-0.021****	**-0.019****	**-0.022****	**-0.021****	**-0.019****
	(0.004)	(0.0038)	(0.004)	(0.0037)	(0.0041)	(0.0039)	(0.004)	(0.0039)	(0.0038)	(0.004)
disruption	**0.033****	**0.038****	**0.031****	**0.039****	**0.026****	**0.034****	**0.039****	**0.041****	**0.033****	**0.033****
	(0.0083)	(0.008)	(0.0086)	(0.0078)	(0.008)	(0.008)	(0.0086)	(0.0083)	(0.0081)	(0.008)
poverty	-0.008	-0.008**	-0.008	-0.006	-0.006	-0.004	-0.010**	-0.008**	-0.004	-0.001
	(0.0042)	(0.004)	(0.0042)	(0.004)	(0.004)	(0.004)	(0.0042)	(0.0041)	(0.004)	(0.004)
unemployment	0.015	0.012	0.003	-0.001	0.005	0.008	0.005	0.004	0.004	-0.005
	(0.0085)	(0.0085)	(0.009)	(0.008)	(0.0084)	(0.008)	(0.0087)	(0.0082)	(0.0081)	(0.0079)
income	0.002	0.005**	0.003**	0.004**	0.003**	0.004**	0.003	0.003**	0.005**	0.003**
	(0.0015)	(0.0015)	(0.0016)	(0.0015)	(0.0014)	(0.0014)	(0.0015)	(0.0015)	(0.0015)	(0.0014)
bus	**0.014****	**0.022****	**0.019****	**0.024****	**0.018****	**0.018****	**0.020****	**0.020****	**0.020****	0.018**
	(0.0036)	(0.0037)	(0.0038)	(0.0035)	(0.0035)	(0.0035)	(0.0038)	(0.0037)	(0.0036)	(0.0034)
elder	-0.001	-0.010	-0.011	0.000	-0.007	-0.002	0.004	-0.005	0.001	0.002
	(0.0059)	(0.0059)	(0.0062)	(0.0059)	(0.0059)	(0.006)	(0.0064)	(0.0059)	(0.0059)	(0.0058)
black	-0.001	-0.001	0.003	-0.001	0.002	-0.001	-0.003	-0.001	-0.001	0.000
	(0.0023)	(0.0022)	(0.0023)	(0.0022)	(0.0022)	(0.0022)	(0.0023)	(0.0022)	(0.0022)	(0.0022)
pop	**-0.188****	**-0.149****	**-0.173****	-0.157**	-0.105**	-0.156**	-0.145**	-0.171**	-0.174**	-0.127**
	(0.0241)	(0.0228)	(0.0237)	(0.0209)	(0.026)	(0.0212)	(0.0249)	(0.0233)	(0.0224)	(0.0261)

	2019					2020				
	01-02	*03-05*	*06-08*	*09-11*	*12*	*01-02*	*03-05*	*06-08*	*09-11*	*12*
female	-0.006	-0.008	-0.005	-0.004	0.000	-0.006	-0.004	-0.006	-0.002	-0.005
	(0.0068)	(0.0067)	(0.007)	(0.0065)	(0.0067)	(0.0064)	(0.0069)	(0.0068)	(0.0066)	(0.0065)
center	-0.005	-0.003	-0.006	0.000	0.002	0.001	-0.003	0.000	0.002	0.007
	(0.0053)	(0.0052)	(0.0053)	(0.0051)	(0.005)	(0.0051)	(0.0054)	(0.0053)	(0.0052)	(0.0051)
fire	-0.137**	-0.142**	-0.110	-0.153**	-0.072	-0.078	-0.126**	-0.118**	-0.078	-0.109**
	(0.0539)	(0.0537)	(0.0574)	(0.0521)	(0.052)	(0.0527)	(0.056)	(0.0543)	(0.0529)	(0.0528)
police	**-0.036****	-0.025	-0.052**	-0.053**	-0.045**	-0.041**	-0.052**	-0.062**	-0.062**	-0.036**
	(0.0177)	(0.017)	(0.018)	(0.017)	(0.0169)	(0.017)	(0.0181)	(0.0178)	(0.0171)	(0.0172)
alpha	**0.504****	**0.510****	**0.571****	**0.481****	**0.372****	**0.459****	**0.541****	**0.510****	**0.495****	**0.379****
	(0.0355)	(0.0341)	(0.0375)	(0.0326)	(0.0319)	(0.033)	(0.0364)	(0.0342)	(0.0335)	(0.0318)
Observations	497	497	497	497	497	497	497	497	497	497
AIC	3922.692	4337.266	4378.427	4245.285	2934.608	3761.153	4221.031	4248.864	4238.270	2973.008
BIC	3990.029	4404.764	4446.177	4313.098	3000.603	3828.619	4288.400	4316.234	4306.114	3039.177
Log likelihood	-1945.3	-2152.6	-2173.2	-2106.6	-1451.3	-1864.6	-2094.5	-2108.4	-2103.1	-1470.5
Pseudo R-squared	0.060	0.058	0.058	0.069	0.065	0.066	0.054	0.064	0.067	0.065

Note: Incidence rate ratios are reported in the results, and standard errors are provided in parentheses; ** $p<0.05$

in 2020/March-May. However, we cannot conclude that this outcome reflects the lockdown because there was also a decrease in 2019/March-May. For 311 events, *ethnic heterogeneity, residential instability, family disruption, median income, bus stations, and proximity to a fire* or a *police station* are the significant variables, and the coefficient of variable *ethnic heterogeneity* has a significant decrease in 2020/June-August. This could be attributed to a delayed impact of the stress for working-class families associated with the lockdown policy and the historical event of the police killing of former Houston resident George Floyd in May 2020.

Discussion

Using a socio-ecological approach, this study examined crime in an urban context, Houston pre-pandemic (2019) compared to the first year of the pandemic restrictions (2020). The overall findings were mixed. For example, unemployment was (negatively) statistically significant in one model for motor vehicle theft in 2019 and not significant in any of the models in 2020. Poverty was statistically significant (positively) in robbery in the 2019 crime models and statistically significant (negatively) motor vehicle theft in the 2020 crime models. This could reflect the impact of more people being home in 2020 and able to guard their vehicles given the tenets of routine activity theory. Nuisance on the property was statistically significant (negatively) in the 2019 311 models and garbage-related events in the 2020 311 models. Violent offenses (aggravated assault and robbery) were related to certain key variables (e.g., median income) while property offenses, such as motor vehicle theft, were related to variables such as residential instability.

Like previous studies such as Shaw and McKay (1942; see Kubrin, 2009) and Pratt and Cullen (2005), this study confirms that factors related to poverty have an impact on crime. For 2019 in Houston, proxies for poverty were significant in impact on both crime and signs of disorder as indicated by the percent Black population, residential instability, and the presence of bus stations. Relatedly also in 2019 family disruption and median income impacted aggravated assault, robbery, and motor vehicle theft numbers. Unemployment was particularly impactful with motor vehicle thefts, but not other offenses. Ethnic heterogeneity a proxy for immigrant presence was significant in 2019 for nuisance on property, dead animal collection, and sewage calls. This is consistent with trends associated with a high renter population as opposed to property owners (Harding *et al*., 2003). There were more observable significant relationships in the 2019 data than in the 2020 data. For 2020, bus stations and the percentage of Blacks remained positively predictive of both crimes and signs of disorder reflecting more crime in lower socio-economic communities. While Houston is a sprawling driving city, in those pockets where the number of bus stations is high and walking more likely, plus residential instability indicates socioeconomic strains, the more persons walk, the more likely they are to see an opportunity for predatory crimes which is supported Yu's (2011) study on bus stops and crime. Hence in this study burglary, motor vehicle theft and robbery numbers were significantly related to bus stations for 2019. This significant relationship increased slightly for 2020 supporting routine activity theory. Lee and Contreras (2021) had similar findings in Los Angeles where the impact of "preexisting social circumstances (i.e., socioeconomic status, residential stability, and racial and ethnic heterogeneity) of neighborhoods with more or less access to amenities within walking distance…might be context-specific" (p. 755). Population density had a negative effect on crimes (which might suggest more guardianship with more persons at home) but a positive effect on signs of disorder which is likely indicative of more persons being at home both contributing to the creation of the signs of disorder and being there to see and report them. Other effects in 2020 were mixed or not clear which given the uniqueness of life that year requires qualitative insights for a more thorough comprehension. Overall, data indicate that a possible difference in the crime and disorder numbers likely reflects shifting levels of guardianship effects with more persons being at home. These findings offer support for situational crime prevention policy approaches given routine activity theory so the next section will explore potential policy implications for situational crimes in urban settings, like Houston.

Policy Implications

The COVID-19 pandemic was a unique event that affected both persons and places, so the place/environment is an important consideration in any attempt to reduce crime. With policy changes such as the closing of bars, restaurants, gyms, movie theatres, and social gathering restrictions, crime opportunities also changed. We find that factors such as bus stations and residential instability are crime opportunities that require situational strategies. As established, crime in urban settings is usually concentrated in a few pocket areas so changes to the structure of such communities are needed. First, the social circumstances of the persons in the area including likely motivations for behaviors and examining community ecology to understand how motivated offenders are accessing their suitable targets are important. Effective crime prevention strategies should include addressing signs of disorder (e.g., garbage-related events). Place-based intervention strategies should be considered, especially where police presence can be increased to deter would-be criminals. However, as indicated in other studies (e.g., see

Maskaly *et al.*, 2021), in-person police training shifted to virtual training, and many officers were not properly trained on how to respond to high-risk populations, so crime likely impacted groups differently. City leaders and local governments may consider increasing funding to areas that have higher poverty rates and bus stations. City leaders should also review current policies, training protocols, and available resources to prepare for similar future situational events, like COVID-19 pandemic, that may have broad-scale impacts on society and persons, especially crime.

Conclusion

Through our time series analysis, we uncovered that the lockdown policy has indeed had a positive impact on specific types of crimes, notably burglary, motor vehicle theft, and robbery. On the flip side, certain crimes, like aggravated assault and 311 events exhibited an increasing trend during the lockdown. Nevertheless, two predictors, namely median income, and the number of bus stations, consistently maintained their significance across all four crime categories and 311 events. Thus shifts in guardianship where offenders and targets may converge in time and place mattered for specific crimes and signs of disorder. Additionally, several less stable predictors show significance in some phases but not in others. Although we have not delved deeply into the analysis of these factors in this study, they warrant further investigation.

As with any study, there are limitations. First, this study only covered two years – 2019 (pre-pandemic) and 2020 (during the pandemic), which is a short look at crime trends and patterns in Houston. Second, given that COVID-19 led to several changes (e.g., lockdowns, stay-at-home orders, travel restrictions, etc.), there may have been personnel shortage so post-pandemic data collection and classification were likely not finalized numbers as utilized in this study. For example, using the availability of a local fire service station and a police station as an indicator of guardianships by mere location may not indicate unique obstacles to service in 2020 when several employees may have been out at the same time due to COVID-19 infections and exposure. Third, the change in the boundaries of the census tract and the number of observation changes suggest caution should be exercised when interpreting findings and comparing both 2019 and 2020 models. Lastly, a quantitative study may not be as in-depth as a qualitative study as residents' perspectives and experiences regarding COVID-19 and crime in the area were not included in the data.

For future studies, a mixed method examination is recommended to provide more insights from people's perspectives regarding their experience with COVID-19 and crime. Future studies should examine post-pandemic data to see if the crime rate changed, remained stable, or returned to pre-pandemic levels. Longitudinal studies to track the long-term effects of the pandemic on urban crime should be conducted. Studies should also look carefully at ecology and interdependent sociological and economic effects given how Houston emerged in 2021 and 2022 from COVID-19 pandemic restrictions as such knowledge would be informative for future crime prevention efforts.

References

Andresen, M. A. (2006). A spatial analysis of crime in Vancouver, British Columbia: A synthesis of social disorganization and routine activity theory. *The Canadian Geographer, 50*(4), 487-502.

Ashby, M. P. J., Bäcker, L., De Cao, E., & Sutherland, A. (2020). COVID-19 and crime: Effects of changes in routine activities and lockdowns on burglary rates in the United Kingdom. *Journal of Quantitative Criminology, 36*(4), 853-880.

Bernasco, W. & Block, R. (2011). Robberies in Chicago: A block-level analysis of the influence of crime generators, crime attractors, and offender anchor points. *Journal of Research in Crime and Delinquency, 48*(1), 33–57

Boman IV, J. H. & Gallupe, O. (2020). Has COVID-19 changed crime? Crime rates in the United States during the pandemic. *American Journal of Criminal Justice, 45,* 537-545. https://doi.org/10.1007/s12103-020-09551-3.

Brantingham, P. J., & Brantingham, P. L. (1993). Nodes, paths, and edges: Considerations on the complexity of crime and the physical. environment. *Journal of Environmental Psychology*, *13(*1), 3-28. https://doi.org/10.1016/S0272-4944(05)80212-9

Braga, A. A., Papachristos, A. V., Hureau, D. M. (2014). The effects of hot spots policing on crime: An updated systematic review and meta-analysis. *Justice Quarterly, 31*(4), 633-663. http://dx.doi.org/10.1080/07418825.2012.673632

Britt, C. L., Rocque, M., & Zimmerman, G. M. (2018). The analysis of bounded count data in criminology. *Journal of Quantitative Criminology, 34*(2), 591–607. https://doi.org/10.1007/s10940-017-9346-9

Campedelli, G. M., Favarin, S., Aziani, A., & Piquero, A. R. (2020). Disentangling community level changes in crime trends during the COVID-19 pandemic in Chicago. *Crime Science, 9*(21), 1-18. https://doi.org/10.1186/s40163-020-00131-8

City of Houston (2022). Facts and Figures (houstontx.gov)

Cohen, L. E., & Felson, M. (1979). Social change and crime rate trends: A routine activity approach. *American Sociological Review, 44*(4), 588-608.

Eck, J. E., Chainey, S., Cameron, J. G., Leitner, M., & Wilson, R. E. (2005). Mapping crime: Understanding hotspots. *National Institute of Justice.* https://www.ojp.gov/pdffiles1/nij/209393.pdf

Errol, Z., Madsen, J. B., & Moslehi, S. (2021). Social disorganization theory and crime in the advanced countries: Two centuries of evidence. *Journal of Economic Behavior and Organization, 191,* 519-537. https://doi.org/10.1016/j.jebo.2021.09.017

Estévez-Soto, P.R. (2021). Crime and COVID-19: effect of changes in routine activities in Mexico City. *Crime Science, 10* (15), 1-17. https://doi.org/10.1186/s40163-021-00151-y

Felson, M., Jiang, S., & Xu, Y. (2020). Routine activity effects of COVID-19 pandemic on burglary in Detroit, March, 2020. *Crime Science, 9,* 1-7. https://crimesciencejournal.biomedcentral.com/articles/10.1186/s40163-020-00120-x

Glaser, E. L., & Sacerdote, B. (1999). Why is there more crime in cities? *Journal of Political Economy, 107*(6), S225-S258. https://www.jstor.org/stable/10.1086/250109

Gregory, E., Hough, Z., Econ, M., & Martinez, I. (2023). Houston area domestic violence providers study initial local Dv data aggregation. https://www.uh.edu/class/ws/irwgs/_docs/2023/dv-providers-study-report-final-feb-2023.pdf

Gramlich, J. (2021). What we know about the increase in U.S. murders in 2020. *Pew Research Center.* https://www.pewresearch.org/short-reads/202

Harding, J., Miceli, T. J. & Sirmans, C. F. (2003. Do owners take better care of their housing than renters? *Real Estate Economics, 28* (4), 663-681. https://doi.org/10.1111/1540-6229.00815

Hastings-Blow, C. (2022). How life during a pandemic may have contributed to homicide in Houston, Texas. *Journal of Family Strengths*, *21(2)* Article 5 (32 pages). https://digitalcommons.library.tmc.edu/jfs/vol21/iss2/5

He, L., Páez, A., & Liu, D. (2017). Built environment and violent crime: An environmental audit approach using Google Street View. *Computers, Environment and Urban Systems, 66,* 83–95. https://doi.org/10.1016/j.compenvurbsys.2017.08.001

Hipp, J. R., Lee, S., Ki, D., & Kim, J. H. (2022). Measuring the built environment with Google Street View and machine learning: Consequences for crime on street segments. *Journal of Quantitative Criminology, 38*(3), 537-565.

Jones, R. W. & Pridemore, W. A. (2019). Toward an integrated multilevel theory of crime at place: Routine activities, social disorganization, and the law of crime concentration. *Journal of Quantitative Criminology, 35,* 543-572. https://doi.org/10.1007/s10940-018-9397-6

Kubrin, C.E. (2009). Social disorganization theory: Then, now, and in the future. In: M. Krohn, A. Lizotte, and G. Hall (eds). *Handbook on Crime and Deviance.* Handbooks of Sociology and Social Research. Springer. https://doi.org/10.1007/978-1-4419-0245-0_12

Kubrin, C. E., Branic, N., & Hipp, J. R. (2022). (Re) conceptualizing neighborhood ecology in social disorganization theory: from a variable centered approach to a neighborhood centered approach. *Crime and Delinquency, 68*(11), 2008-2032.

Lander, B. (1954). *Towards an understanding of juvenile delinquency*. Columbia University Press.

Lee, N, & Contreras, C. (2021). Neighborhood walkability and crime: Does the relationship vary by crime type? *Environment and Behavior, 53* (7), 753-786.

Li, Y., Hyder, A., Southerland, L.T., Hammond, G., Porr, A., & Miller, H. J. (2020). 311 service requests as indicators of neighborhood distress and opioid use disorder. *Scientific Reports,* **1**0, 19579. https://doi.org/10.1038/s41598-020-76685-z

Liu, L., Chang. J., Long, D., & Liu, H. (2022). Analyzing the impact of COVID-19 lockdowns on violent crime. *International Journal of Environmental Research and Public Health, 19*(23), 1-10. doi: 10.3390/ijerph192315525.

Location inc. (2022). Houston crime rates and statistics. Neighborhood scouts. https://www.neighborhoodscout.com/tx/houston/crime

Luo, F., Ren, L., & Zhao, J. S. (2016). Location-based fear of crime: A case study of Houston Texas. *Criminal Justice Review, 41*(1)75-97. https://doi.org/10.1177/0734016815623035

Maskály, J., Ivković, S. K., & Neyroud, P. (2021). Policing the COVID-19 pandemic: Exploratory study of the types of organizational changes and police activities across the globe. *International Criminal Justice Review*, *31*(3), 266 285. https://doi.org/10.1177/10575677211012807

MeKouar, D. (2022). Why homicide rates in the US spiked 30% during COVID pandemic. B https://www.voanews.com/a/why-homicide

Meyer, M., Hassafy, A., Lewis, G., Shrestha, P., Haviland, A. M. & Nagin, D. S. (2022). Changes in crime rates during the COVID-19 pandemic. *Statistics and Public Policy*, *9*(1), 97-109, DOI: 10.1080/2330443X.2022.2071369

Ndjila, S., Lovasi, G.S., Fry, D., & Friche, A. A. (2019). Measuring neighborhood order and disorder: A rapid literature review. *Current Environmental Health Reports,* 6, 316–326. https://doi.org/10.1007/s40572-019-00259-z

O'Brien, D. T. (2019). The action is everywhere, but greater at more localized spatial scales: Comparing concentrations of crime across addresses, streets, and neighborhoods. *Journal of Research in Crime and Delinquency, 56*(3), 339-377.

Oliviera, M. (2021). More crime in cities? On the scaling laws of crime and the inadequacy of per capita rankings—a cross-country study. *Crime Science, 27*(10), 1-13. https://doi.org/10.1186/s40163-021-00155-8

Osgood, D. W. (2000). Poisson-based regression analysis of aggregate crime rates. *Journal of Quantitative Criminology, 16(1*), 21–43. https://doi.org/10.1023/A:1007521427059

Ousey, G. (2000). Explaining regional and urban variation in crime: A review of research. *Criminal Justice, 1,* 261-308. https://www.semanticscholar.org/paper/Explaining-Regional-and-Urban-Variation-in-Crime-%3A-Ousey/bb4e6d6acab15fd800ababf1263c28b041a600f9

Petersen N. (2016). Neighborhood context and media constructions of murder: A multilevel analysis of homicide newspaper coverage in Los Angeles County. *Homicide Studies*, *20*(1), 25–52.

Pratt, T. C. & Cullen, F. T. (2005). Assessing macro-level predictors and theories of crime: A meta-analysis. *Crime and Justice, 32,* 273-449.

Roncek, D. W., & Maier, P. A. (1991). Bars, blocks, and crimes revisited: Linking the theory of routine activities to the empiricism of "hot spots". *Criminology 29*(4), 725–753.

Rosenfeld, R. & Lopez, E. (2021, September). Pandemic, social unrest, and crime in U.S. Cities: September 2021 Update. Washington, D.C.: Council on Criminal Justice. https://counciloncj.org/wp-content/uploads/2021/10/Pandemic-Social-Unrest-and-Crimein-US-Cities-September-2021-Update.pdf

Sampson, R. J., & Raudenbush, S. W. (2001, February). *Disorder in urban neighborhoods—Does it lead to crime?* Research Brief. U.S. Department of Justice, Office of Justice Programs, National Institute of Justice. https://www.ojp.gov/pdffiles1/nij/186049.pdf

Sharkey, P. (2013). *Stuck in place: Urban neighborhoods and the end of progress toward racial equality*. Chicago: University of Chicago Press.

Shaw, C. R., & McKay, H. D. (1942). *Juvenile delinquency and urban areas*. Chicago: University of Chicago Press.

Spano, R. & Freilich, J. D. (2009). An assessment of the empirical validity and conceptualization of individual level multivariate studies of lifestyle/routine activities theory published from 1995-2005. *Journal of Criminal Justice, 37*(3), 305-314.

Skogan, W. (2015). Disorder and decline: The state of research. *Journal of Research in Crime and Delinquency, 52*(4), 464-485.

Skogan, W. G. (2012). Disorder and crime. In B. C. Welsh & D. P. Farrington (Eds.), *The Oxford Handbook of Crime Prevention* (pp. 173-188). New York: Oxford University Press.

Smith, S., Ferguson, C. J., & Henderson, H. (2021). An exploratory study of environmental stress in four high violent crime cities: What sets them apart? *Crime and Delinquency,* 1-23. Advanced online publication.

Song, G., Zhang, Y., Bernasco, W., Cai, L., Liu, L., Qin, B., & Chen, P. (2021). Residents, employees and visitors: Effects of three types of ambient population on theft on weekdays and weekends in Beijing, China. *Journal of Quantitative Criminology*. https://doi.org/10.1007/s10940-021-09538-1

Stickle, B., Felson, M. (2020). Crime rates in a pandemic: The largest criminological experiment in history. *American Journal of Criminal Justice,* 45, 525–536. https://doi.org/10.1007/s12103-020-09546-0

Ward, K. C., Kirchner, E. E., & Thompson, A. J. (2018). Social disorganization and rural/urban crime rates: A county level comparison of contributing factors. *International Journal of Rural Criminology, 4*(1), 43-65.

Weisburd, D. (2012). Bringing social context back into the equation. *Criminology and Public Policy, 11*(2), 317–326. https://doi.org/10.1111/j.1745-9133.2012.00810.x

Weisburd, D. & Telep, C. W. (2014, February). Police and the microgeography of crime: Scientific evaluations on the effectiveness of hot spots and places. Inter-American Development Bank. Institutions for Development Sector. Technical note. No. IDB-TN630. https://publications.iadb.org/en/police-and-microgeography-crime-scientificevaluations-effectiveness-hot-spots-and-places

Wells, W., & Wu, L. (2011). Proactive policing effects on repeat and near-repeat shootings in *Houston. Police Quarterly, 14*(3), 298-319.

Wells, W., Wu, L., & Ye, X. (2012). Patterns of near-repeat gun assaults in Houston. *Journal of Research in Crime and Delinquency, 49(2*), 186-212.

Wheeler, A. P., & Reuter, S. (2020). Redrawing hot spots of crime in Dallas, Texas. *Police Quarterly, 24*(2), 159-184. https://doi.org/10.1177/1098611120957948

Wo, J. C. (2019). Understanding the differential effects of land uses on crime: An examination across Philadelphia neighborhoods. *The British Journal of Criminology*, 59(6), 1432–1454. https://doi.org/10.1093/bjc/azz019

Yang, M., Chen, Z., Zhou, M., Liang, X., & Bai, Z. (2021). The impact of COVID-19 on crime: A spatial temporal analysis in Chicago. *ISPRS International Journal of Geo-Information*, *10*(3):152. https://doi.org/10.3390/ijgi10030152

Yu, S. V. (2011). Do bus stops increase crime opportunities? El Paso: LFB Scholarly Publication.

Zhang, Y., Cai, L., Song, G., Liu, L., & Zhu, C. (2022). From residential neighborhood to activity space: The effects of educational segregation on crime and their moderation by social context. *Annals of the American Association of Geographers, 112*(8), 2393–2412. https://doi.org/10.1080/24694452.2022.206079