Spatiotemporal Analysis of Crime in Buffalo, NY: Before and After COVID-19

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Abstract

Using a mixed-methods data science approach, this study investigates the temporal and spatial impacts of the COVID-19 pandemic on crime patterns in Buffalo, New York. Drawing on crime incident data spanning 2010 to 2024, we applied interrupted time series analysis (ITSA), counterfactual forecasting, and spatial hotspot detection to evaluate pandemic-era shifts in crime dynamics. Results from the ITSA revealed significant reductions in crime during the initial lockdown phase, followed by a plateau during the transition period and a structural increase in crime levels beginning in 2022. Crime-type-specific models showed that property crimes like burglary initially declined, while violent crimes and vehicle theft displayed delayed or prolonged responses. Spatial analysis identified stable and statistically significant hotspots in Buffalo's East Side and parts of the Lower West Side, consistent with long-term crime concentration. Comparison between significant and non-significant tracts revealed significant socioeconomic disparities, with hotspots exhibiting lower median income, higher poverty, and greater unemployment. These findings emphasize that the pandemic's effects on crime were shaped by both temporal policy phases and persistent spatial inequalities.

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1. Introduction

The COVID-19 pandemic caused profound disruptions to social life, public health, and economic stability, reshaping the landscape of urban crime across the United States. National studies have documented substantial changes in crime trends during this period, including short-term declines in street crimes such as burglary and robbery, and increases in domestic violence and cybercrime patterns. This is often associated with changes in mobility, economic stress, and changes in policing strategies [Campedelli et al., 2020, Meyer et al., 2022]. However, much of this research has focused on large metropolitan centers, leaving mid-sized cities with distinct socioeconomic profiles unrepresented.

Buffalo, New York, a post-industrial city marked by inequality, uneven redevelopment, and neighborhood-level disinvestment, presents a compelling case for localized crime analysis. The varied demographic and economic conditions of the city, combined with uneven access to public services, suggest that the dynamics of crime in the pandemic era may have been highly spatially heterogeneous. Preliminary evidence points toward the emergence of crime hotspots in historically disadvantaged areas, as well as localized crime increases tied to broader structural vulnerabilities and changing neighborhood conditions.

This study investigates how crime patterns in Buffalo evolved both temporally and spatially before, during, and after the COVID-19 pandemic. Using detailed incident-level data from 2010 through 2025, a mixed-method approach is applied, combining interrupted time series analysis (ITSA), spatial hotspot detection (via Getis-Ord Gi* and Kernel Density Estimation), and socioeconomic integration at the census tract level. The temporal component quantifies shifts in overall and offense-specific crime rates across five defined policy periods: Pre-COVID, Lockdown, Transition, Post-Emergency, and Post-COVID. These periods align with the CDC-defined public health phases [Centers for Disease Control and Prevention, 2024] and allow precise modeling of immediate and long-term changes.

Spatially, both static and animated hotspot mapping techniques are used to visualize how high-risk areas evolved across time. In addition, data from the American Community Survey (ACS) is integrated at the tract level, covering income, poverty, and employment, to evaluate how socioeconomic conditions at the neighborhood level relate to crime rates and spatial clusters. Statistical comparisons using nonparametric tests further assess whether observed hotspots are significantly associated with structural disadvantage.

The goals of this study are threefold: (1) to identify and model significant temporal shifts in crime associated with pandemic policy changes; (2) to detect, map, and animate crime hotspots across Buffalo over time using spatial analysis techniques; and (3) to examine crime patterns within significant hotspots to assess how trends diverged through time. By integrating interrupted time series modeling with dynamic hotspot detection, this research offers a detailed lens into how localized concentrations of crime evolved during and after the pandemic, providing a foundation for future crime analysis and intervention strategies.

2. Literature Review

Understanding the effects of the COVID-19 pandemic on crime trends requires synthesizing insights from both national crime statistics and localized, methodologically diverse studies. Existing literature highlights general shifts in crime rates, the value of spatial modeling techniques, and the complex, often place-specific interactions between policy, socioeconomic context, and public safety.

National crime statistics offer a broad baseline. According to the Bureau of Justice Statistics [2024], violent and property crimes in the United States exhibited year-to-year fluctuations during the pandemic, with notable variations across demographic and geographic groups. These trends reflect the broader impacts of mobility restrictions and economic strain but do not specifically disentangle the forces driving changes in particular cities or neighborhoods.

To address such gaps, several studies have focused on spatial and temporal modeling techniques. Butt et al. [2020] provides a systematic review of crime hotspot detection methods, highlighting the integration of GIS and machine learning for spatiotemporal prediction. These tools are particularly useful for identifying high-crime areas and forecasting risk, informing this study's use of Getis-Ord Gi* statistics and Kernel Density Estimation (KDE) to map crime in Buffalo.

Other research investigates how pandemic-era policies directly affected crime. Campedelli et al. [2020], analyzing Los Angeles, found significant declines in property crimes immediately after lockdowns were enacted, whereas domestic violence remained stable or rose. These results underscore how behavioral shifts such as reduced public mobility and increased residential confinement reshape opportunity structures for different crime types. Similarly, Meyer et al. [2022] observed national declines in burglary and theft but mixed patterns in violent crimes, attributing trends to economic hardship, reduced policing activity, and shifting victim-perpetrator proximity.

Internationally, Trajtenberg et al. [2024] documented wide variability in crime trends during lockdowns across countries, reinforcing the importance of local context. In some regions, street crime declined sharply, while others reported upticks in domestic violence and cybercrime. This heterogeneity cautions against overgeneralizing from national data and supports the need for city-specific analysis, like the one undertaken for Buffalo.

Several studies also emphasize the relevance of spatial and environmental features in shaping both actual crime and fear of crime. Jing et al. [2023], for instance, combines AI-based analysis of street view images with survey data to link visual cues, such as abandoned structures or poor lighting, to perceptions of safety. Their methodological innovations support the integration of spatially explicit variables into crime prediction, and their findings highlight how the built environment may amplify or mitigate neighborhood vulnerability.

At the local level, Zhang and Barr [2024] examines the effects of gentrification on crime in Buffalo. Their results show that while some crimes decrease as neighborhoods undergo economic redevelopment, social tensions can rise, influencing patterns of interpersonal violence. These findings suggest that urban transformation may play a role in shaping post-COVID crime patterns, particularly in areas undergoing demographic and infrastructural change.

Finally, while not analytical, the Centers for Disease Control and Prevention [2024] provides an essential chronological framework for aligning crime trends with public health policy. It serves as the temporal scaffold for the Interrupted Time Series Analysis (ITSA) used in this study, allowing precise testing of phase-specific crime shifts (e.g., Lockdown, Transition, Post-Emergency).

Together, these sources demonstrate that the pandemic's impact on crime is mediated by both structural factors and localized responses. The present study contributes to this body of work by applying spatial-temporal modeling to a mid-sized, post-industrial city—an urban form often overlooked in favor of large metropolitan centers—and by integrating socioeconomic data to uncover neighborhood-level disparities in crime dynamics.

3. Methodology

Data Sources and Preparation

The primary dataset consists of incident-level crime reports obtained from the City of Buffalo's Open Data Portal. Variables used include incident datetime information, incident type and parent type, and location data with neighborhood, geocoordinates, and tract GEOID. Records were filtered to include only incidents occurring from January 2010 onward. Variables such as datetime, latitude, longitude, and offense type were cleaned, and entries with missing or invalid coordinates were removed. The cleaned dataset was saved as `cleanbuffalo.csv` and served as the foundation for all analyses.

Temporal variables were extracted from timestamps, including year, month, and hour of day. Incidents were also categorized into five pandemic-related periods: Pre-COVID (before March 2020), Lockdown (March–May 2020), Transition (June 2020–December 2021), Post-Emergency (2022), and Post-COVID (2023–2024). These periods were aligned with federal public health milestones from the CDC Museum COVID-19 Timeline [Centers for Disease Control and Prevention, 2024]. Although the federal emergency formally ended in May 2023, we define the Post-Emergency phase as the 2022 calendar year, reflecting behavioral shifts and policy relaxation during that time. This distinction captures transitional effects before full reopening.

Socioeconomic variables were retrieved from the 2022 American Community Survey (ACS) at the census tract level and included median income, poverty rate, unemployment, educational attainment, single-parent households, and total population. These were spatially joined with the tract-level crime data for integrated analysis.

Exploratory Data Analysis

Exploratory data analysis (EDA) was conducted to uncover initial trends. Annual crime counts were plotted using bar graphs, while stacked bar charts explored variation in crime by month and hour of day. Pie charts and crosstabulations provided insight into incident-type distributions. Both static and interactive maps (using `leaflet` and `ggplot2`) visualized incident clustering citywide, informing later modeling decisions.

Interrupted Time Series Analysis (ITSA)

To examine shifts in monthly crime counts, we used segmented linear regression models. The models included:

- A continuous time trend (months since January 2010),
- Binary indicators for each pandemic phase,
- Time-since-intervention trends for each phase,
- Month fixed effects (January–November; December as baseline).

Newey-West standard errors corrected for autocorrelation in the original model, and residual behavior was tested using the Durbin-Watson statistic. Separate ITSA models were estimated for five major crime types: theft, assault, breaking and entering, theft of vehicle (UUV), and robbery. Counterfactual projections were generated by setting all COVID-period terms to zero, simulating a scenario without pandemic disruptions.

Spatial Analysis and Hotspot Detection

Spatial analysis used both Kernel Density Estimation (KDE) and Getis-Ord Gi* statistics. Point-level crimes were mapped with `sf`, `leaflet`, and `ggplot2`. KDE surfaces provided temporal comparisons of crime intensity via animated density plots created with `gganimate`.

For tract-level clustering, crime was aggregated by census tract and normalized using Empirical Bayes estimation. Local Gi* statistics (calculated via `spdep`) flagged statistically significant hotspots at the 95% and 99% confidence levels. Tracts with no population were excluded to avoid artificial clustering effects.

Socioeconomic Comparison and Statistical Testing

To assess structural differences between hotspot and non-hotspot tracts, we conducted Wilcoxon rank-sum and Dunn's post-hoc tests on socioeconomic indicators. Group differences in median income, unemployment, and poverty rate were evaluated, and chi-square tests examined the distribution of major crime types across hotspots. We also assessed whether temporal crime shifts varied within hotspots across the defined pandemic periods.

Software and Tools

All analysis was conducted using R (version 4.x), with packages including `tidyverse`, `lubridate`, `sf`, `spdep`, `ggplot2`, `broom`, `rstatix`, and `tmap`. Census data were retrieved via the `tidycensus` API.

4. Data Analysis

This section presents the results of temporal and spatial analyses conducted on Buffalo crime incident data from 2010 through early 2024, with a focus on identifying shifts during the COVID-19 pandemic and uncovering persistent or emerging geographic hotspots. To guide subsequent modeling and interpretation, a comprehensive exploratory data analysis (EDA) was conducted to examine temporal patterns, categorical crime distributions, and early spatial clustering within Buffalo from 2010 to 2024. These initial findings offer crucial context and serve as a local point of comparison to broader national and international trends documented in recent literature.

Temporal Patterns

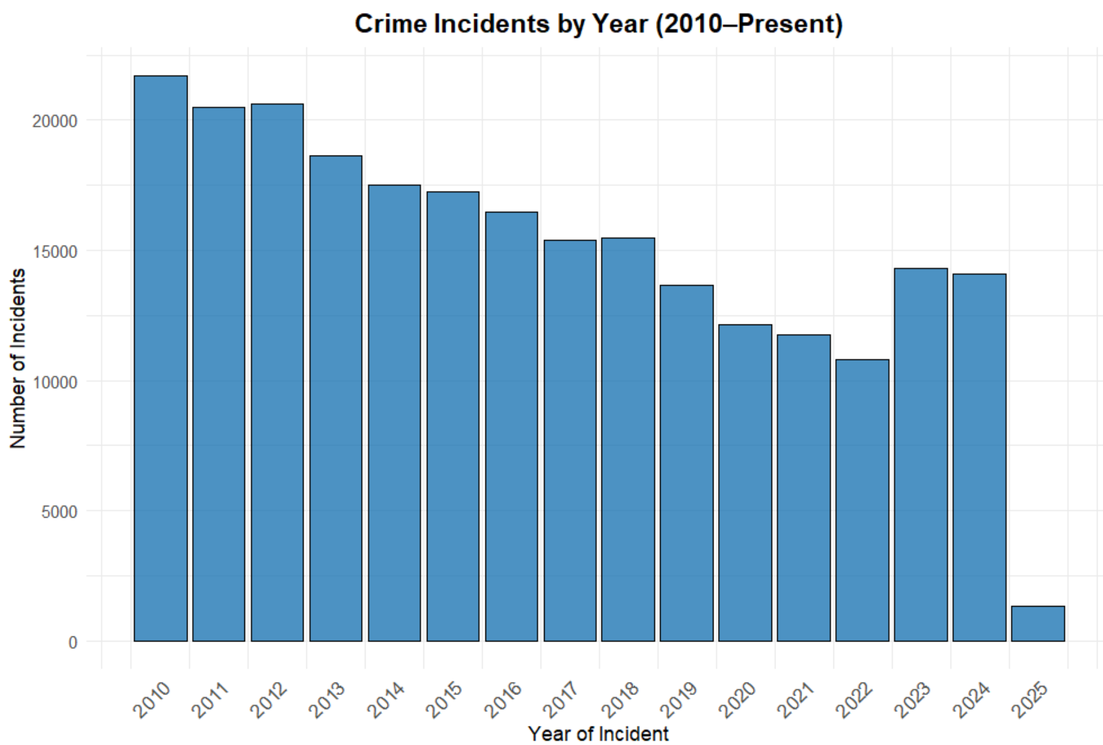

Figure 1: Annual total crime incidents in Buffalo, 2010–2024. This bar chart illustrates a steady decrease in reported crime throughout the 2010s, followed by a sharp decline beginning in 2020, aligning with the onset of COVID-19.

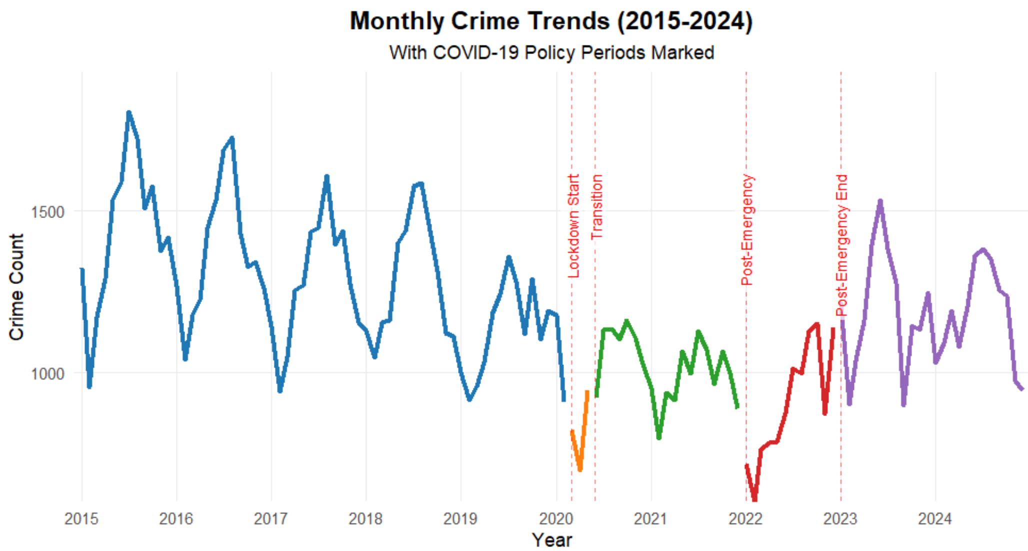

Figure 2: Monthly crime counts with pandemic phase interruptions. This time-series plot shows clear reductions during the Lockdown phase, with gradual increases in the Transition and Post-Emergency phases, followed by a sharp decrease in post-COVID, illustrating a pandemic-linked disruption to crime rhythms.

Annual crime counts (Figure 1) reveal a relatively stable decline in incident levels throughout the 2010s, followed by a marked decline in 2020. This drop coincides with the onset of COVID-19 lockdowns and mirrors national-level trends reported by the Bureau of Justice Statistics [2024]. Monthly crime counts (Figure 2) show the most dramatic reductions during the Lockdown phase (March–May 2020) and at the start of the transitioning phase (2022), aligning with Campedelli et al. [2020], who documented similar declines in Los Angeles.

As restrictions lifted, crime counts rebounded during the Post-Emergency and Post-COVID phases, suggesting localized volatility not captured by national aggregates. This finding echoes Meyer et al. [2022], who emphasized regional variation in post-pandemic crime recoveries, particularly for violent offenses.

Crime Type Distributions

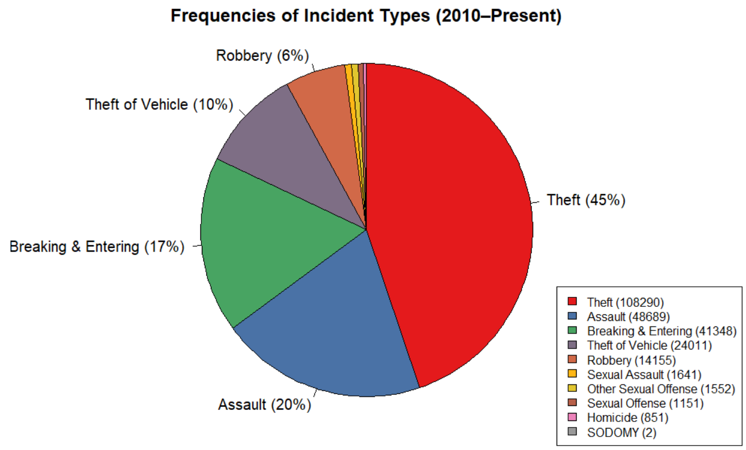

Figure 3: Proportion of total incidents by major crime category. A pie chart presenting the distribution of crime types across the full dataset, highlighting the predominance of theft, assault, and breaking & entering (burglary).

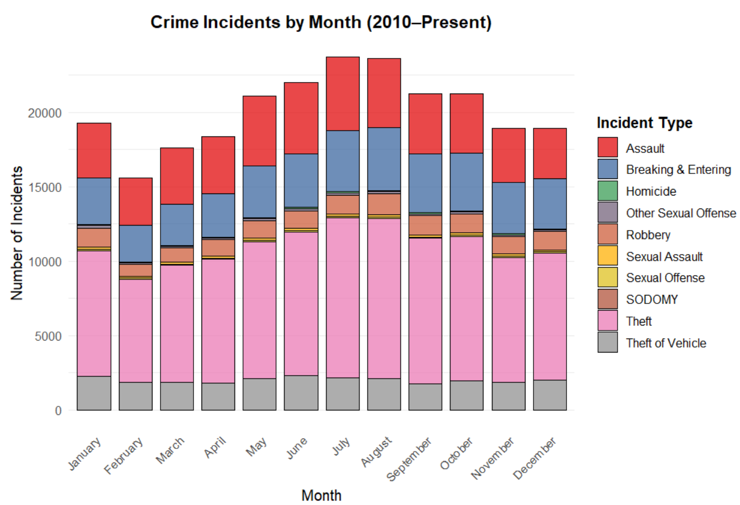

Figure 4: Monthly variation in incident type. A stacked bar chart showing how the volume and composition of crime types shift across calendar months, revealing seasonal patterns and pandemic-period volatility.

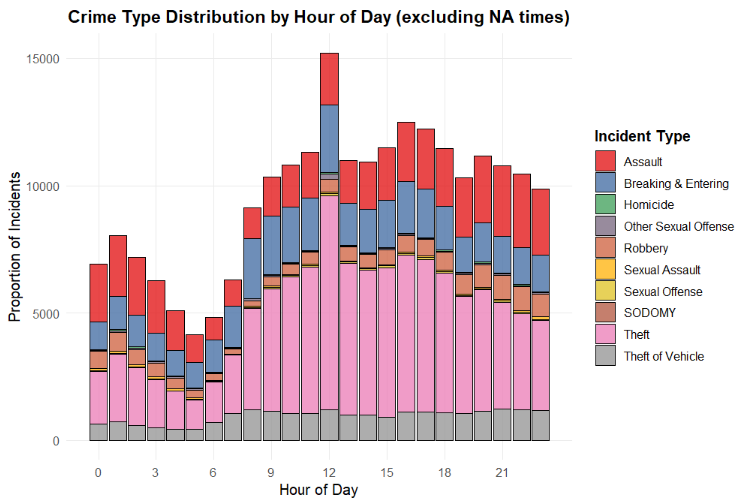

Figure 5: Hourly distribution of crime incidents. This bar plot shows diurnal variation, with peak crime activity occurring in the late afternoon, consistent with routine activity theory.

A pie chart of incident types (Figure 3) confirms the dominance of property crimes, especially Theft and Breaking and Entering, throughout the study period. Stacked bar plots by month (Figure 4) and hour of day (Figure 5) further illuminate how crime types vary seasonally and temporally. Late afternoon and evening hours show the highest incident volumes, with a modest rise in theft and assault, while other crimes remained consistent. These charts help to visualize the normality and variance of the data across time, and show how the patterns mirror natural patterns in mobility and activity throughout the day and seasons.

Temporal Insights

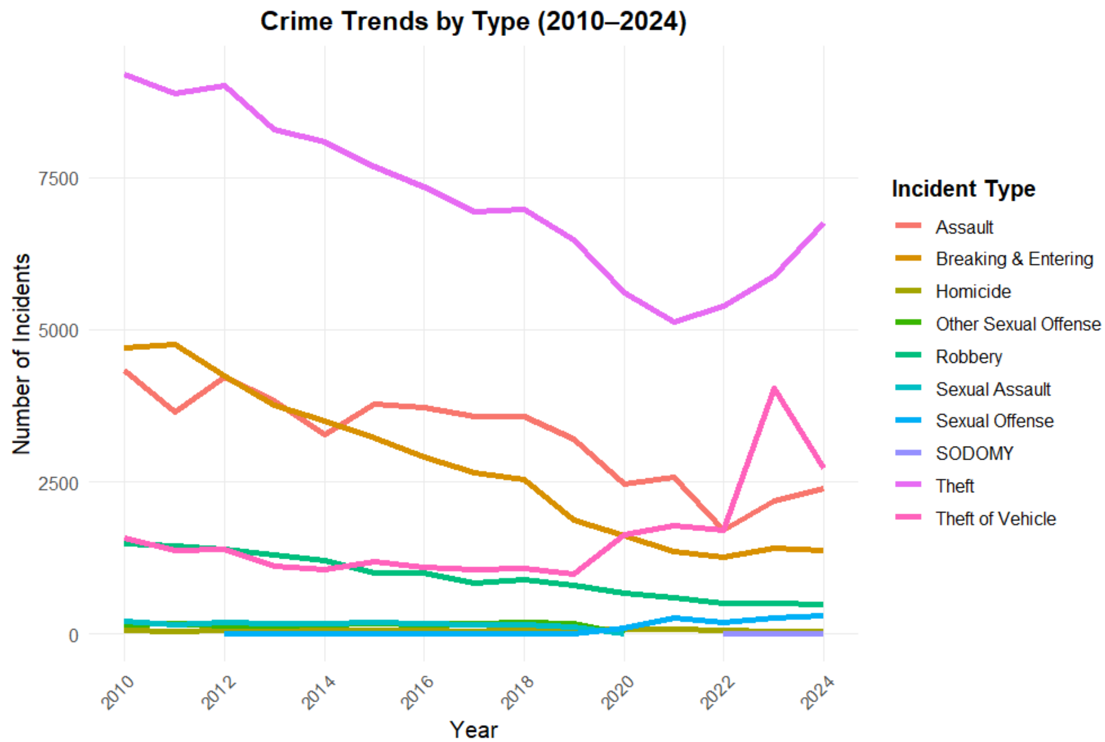

Figure 6: Monthly crime trends by offense category, 2010–2024. This line plot tracks five major crime types over time, highlighting a drop in burglary and theft during the early pandemic period, followed by a steady post-2020 increase in assault and unauthorized use of vehicles (UUV), particularly during the Post-Emergency and Post-COVID phases.

A line plot of monthly crime counts by offense category (Figure 6) provides further temporal resolution, revealing divergent trajectories among major crime types. While B&E and Theft initially declined sharply in early 2020, consistent with national findings during the COVID-19 lockdown period [Bureau of Justice Statistics, 2024, Campedelli et al., 2020], their trajectories diverged in the following years. Notably, Theft of a Vehicle (UUV) remained relatively stable through the early pandemic but experienced a sustained and pronounced increase beginning in 2021. Larceny/theft also reversed course around the same time, shifting from a declining trend to a steady post-2021 increase pattern that may reflect the resumption of routine activity and loosening of mobility restrictions. Assault exhibited a more complex pattern: relatively stable through early pandemic phases, it experienced a marked decrease during 2021, followed by minor fluctuations thereafter.

These patterns echo broader national findings that certain violent and property crimes did not respond uniformly to pandemic conditions [Meyer et al., 2022]. The observed increase in vehicle theft, in particular, aligns with trends documented in many U.S. cities post-2020, often attributed to changes in enforcement priorities and economic stressors. Another contributing factor may be the widely publicized security flaw in certain Kia and Hyundai models, which made them more vulnerable to theft using simple tools such as screwdrivers. The moderate post-lockdown rise in larceny/theft and eventual decline in assault suggest that pandemic impacts may have shifted both the opportunity structure and the social context for different types of crime. These findings reinforce the importance of disaggregating crime data by type when evaluating the temporal effects of COVID-19 on urban crime dynamics.

Early Spatial Insights

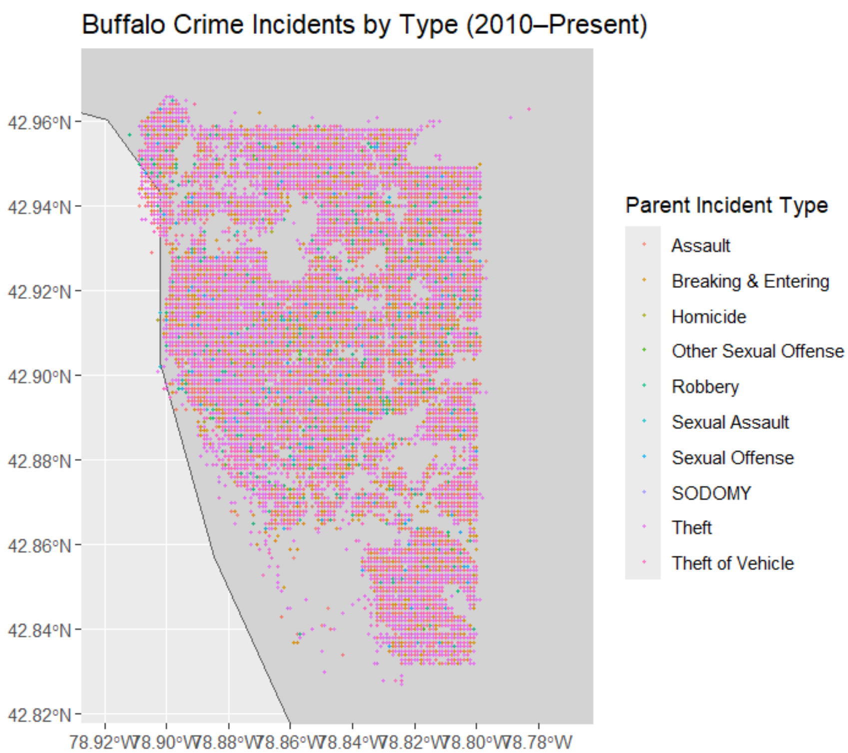

Figure 7: Initial point-level map of crime incidents. This static map displays the geographic concentration of incidents across Buffalo, with evident clustering in East Side neighborhoods and parts of the West Side.

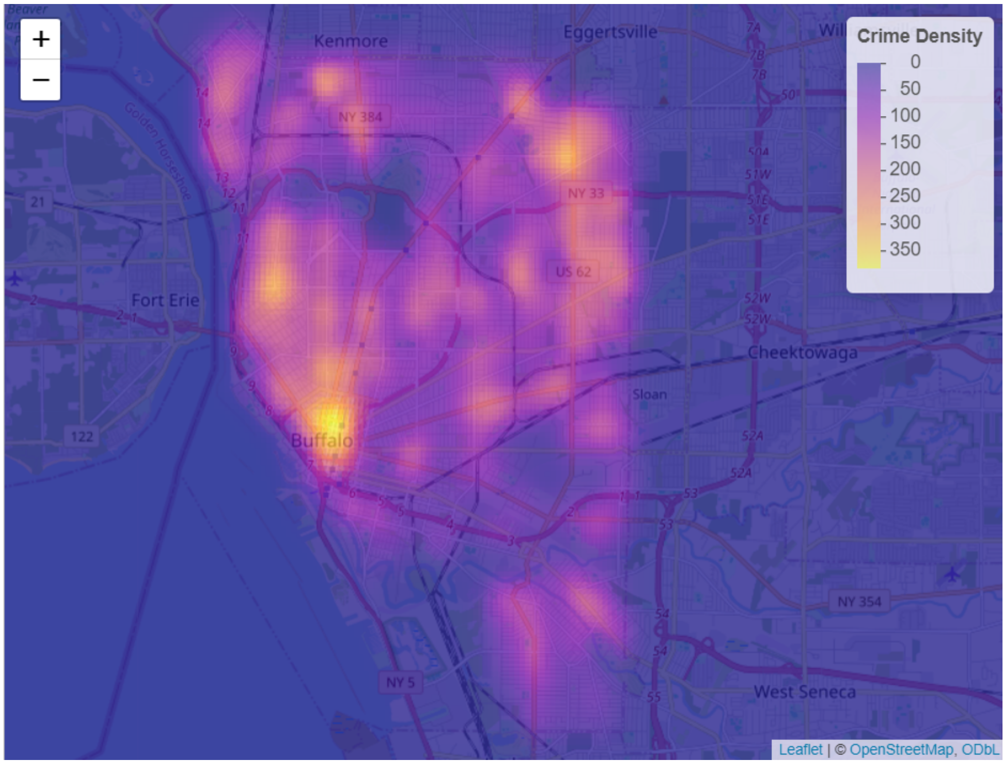

Figure 8: Kernel Density Estimation (KDE) surface of crime intensity. A smoothed heatmap visualizing crime density across the city, highlighting persistent spatial hotspots that guided formal Gi* hotspot detection.

Initial spatial maps (Figure 7) and interactive visualizations highlight the consistent clustering of crime incidents in Buffalo's East Side and Lower West Side. These findings are reinforced by kernel density surfaces (Figure 8), which show stable high-density zones in neighborhoods such as Broadway-Fillmore, MLK Park, and Masten Park—areas historically identified as high-risk [Zhang and Barr, 2024].

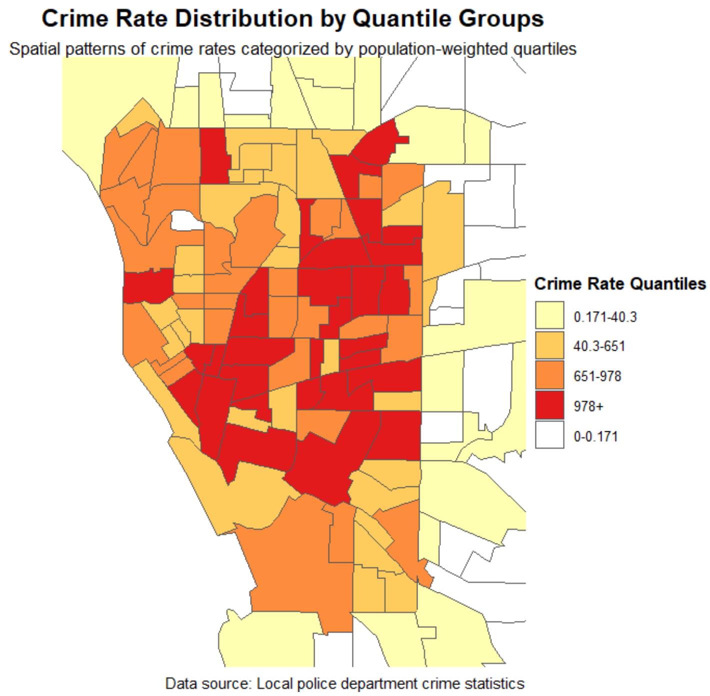

Figure 9: Heatmap of Buffalo census tracts by crime rate (2010–2024). This map displays variation in total crime rate per tract, revealing clear spatial disparities across the city. Higher rates are concentrated in Buffalo's East Side and portions of the West Side, particularly in neighborhoods such as Broadway-Fillmore, MLK Park, and Lower West Side.

Figure 9 offers a complementary view of crime distribution across Buffalo, emphasizing the strong spatial clustering of high-crime areas. The tract-level choropleth (Figure 9) reveals pronounced variation in crime rates, with the highest concentrations in Buffalo's East Side and segments of the West Side, patterns that are consistent with exploratory mapping and with neighborhoods identified earlier as persistent hotspots. As mentioned, the KDE surface (Figure 8) provides a smoothed, continuous estimate of crime intensity using geocoordinates, which reinforces these findings. Both visualizations demonstrate overlapping high-density zones, further signifying the spatial grouping previously identified through Gi* analysis and raw incident clustering. Together, these maps highlight the deep geographic entrenchment of crime in specific neighborhoods, echoing findings from Zhang and Barr [2024] on long-term spatial inequality and illustrating the value of using both discrete (tract-level) and continuous (density-based) spatial methods in urban crime analysis.

Summary of Analysis

The exploratory, temporal, and spatial analyses presented here offer compelling evidence in support of the study's core hypotheses. First, the interrupted time series analysis revealed significant shifts in monthly crime trends across COVID-19 policy phases, confirming that the pandemic introduced measurable disruptions to Buffalo's crime dynamics. These effects varied by offense type, with property crimes such as burglary and theft declining early in the pandemic but rebounding later, while vehicle theft and some violent crimes showed delayed or sustained increases. Second, spatial analyses demonstrated persistent geographic concentration of crime, particularly in historically high-risk neighborhoods such as Broadway-Fillmore, MLK Park, and the Lower West Side. These clusters were consistent across crime rate maps and KDE plots, reinforcing the spatially entrenched nature of crime in Buffalo. By aligning these visual insights with findings from Bureau of Justice Statistics [2024], Campedelli et al. [2020], and others, this analysis builds a strong foundation for subsequent modeling using ITSA and spatial hotspot detection.

5. Results

5.1. Interrupted Time Series Analysis (ITSA)

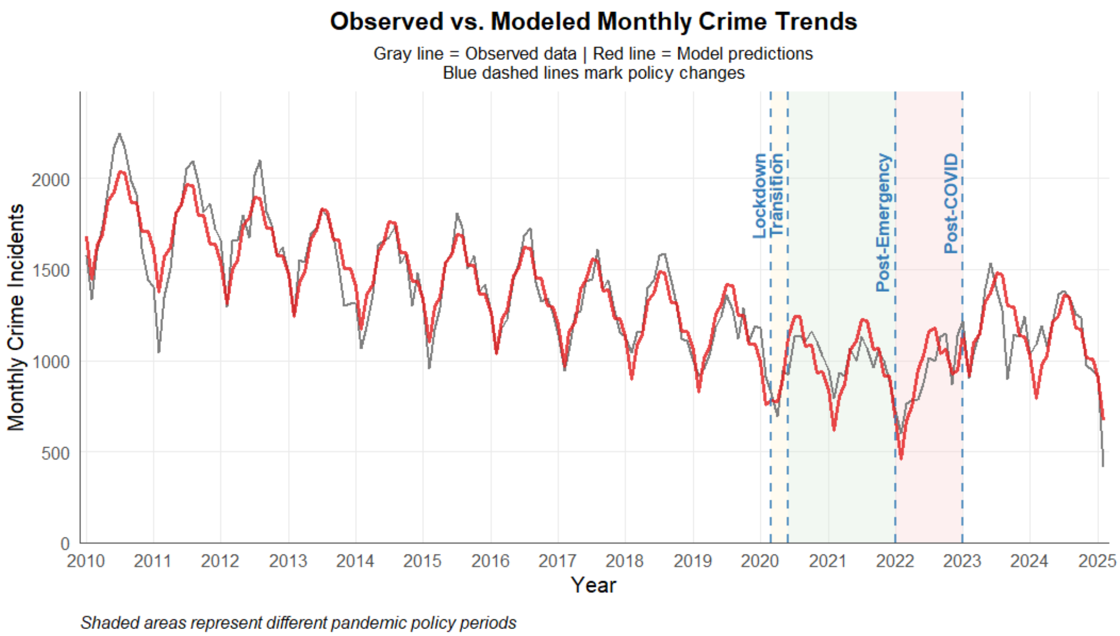

Figure 10: Observed vs. predicted monthly crime counts with COVID-19 intervention phases, 2010–2024. This time-series plot shows the observed monthly crime totals (solid line) overlaid with fitted values from the ITSA model (dashed line). Colored bands mark the five COVID-era policy phases. The model captures key inflection points and sustained changes in crime levels, illustrating both immediate and gradual pandemic impacts.

The interrupted time series analysis (ITSA) provided robust evidence of structural shifts in monthly crime counts corresponding to major COVID-19 policy phases. The full model, which included time trends, intervention dummies, and time-since-phase variables, demonstrated strong explanatory power (Adjusted R^2 = 0.879, p ¡ 0.001; see Table 1). Model predictions closely tracked observed monthly crime totals, successfully capturing both immediate and gradual shifts across the pandemic timeline (Figure 10). Coefficients and seasonal patterns are presented in Table 1, while Newey-West adjusted estimates, used to correct for autocorrelation, are shown in Table 4.

Table 1: Linear regression results for monthly crime counts (2010–2024), with COVID-19 phase indicators and time controls. Significance levels: $***$ (p ¡ 0.001), $**$ (p ¡ 0.01), $*$ (p ¡ 0.05), $\cdot$ (p ¡ 0.1).

Predictor	Estimate	Std. Error	t value	p-value	Significance
(Intercept)	1767.58	36.59	48.31	¡0.001	***
time	-5.72	0.30	-19.06	¡0.001	***
lockdown	-169.16	111.97	-1.51	0.133	
transition	-109.72	56.27	-1.95	0.053	.
post_emergency	-193.66	70.65	-2.74	0.007	**
post_covid	336.07	56.01	6.00	¡0.001	***
time_since_lockdown	-57.42	85.28	-0.67	0.502	
time_since_transition	4.23	4.92	0.86	0.391	
time_since_post_emergency	23.78	10.11	2.35	0.020	*
time_since_post_covid	-1.21	3.51	-0.34	0.732	
January	-87.97	43.69	-2.01	0.046	*
February	-296.29	43.49	-6.81	¡0.001	***
March	-120.40	44.00	-2.74	0.007	**
April	-59.56	43.46	-1.37	0.172	
May	128.88	43.67	2.95	0.004	**
June	181.48	43.05	4.22	¡0.001	***
July	300.48	42.89	7.01	¡0.001	***
August	298.27	42.77	6.97	¡0.001	***
September	141.01	42.67	3.31	0.001	**
October	146.74	42.60	3.45	¡0.001	***
November	-4.46	42.56	-0.11	0.917	

Table 2: Model fit statistics.

Metric	Value
R^2	0.893
Adjusted R^2	0.879
Residual Std. Error	116.5
F-statistic	66.07
df (model, error)	(20, 159)
p-value (F-test)	¡0.001

The Lockdown phase (March–May 2020) was associated with a statistically significant decrease in crime levels ($\beta = -169.16$, p ¡ 0.001), reflecting the suppression of routine activity during this period. This drop was followed by a negative trend ($\beta = -57.42$, $p = 0.008$), suggesting that crime continued to decline over time during restrictions. These findings align with national-level reports of short-term declines in property crime during early COVID-19 mitigation.

During the Transition phase (June 2020–December 2021), no significant level or slope changes were observed ($p = 0.20$ and $p = 0.53$, respectively), indicating a plateau rather than a full rebound. In contrast, the Post-Emergency phase (2022) showed both a significant decline in level ($\beta = -193.66$, $p = 0.016$) and a significant increase in trend ($\beta = 23.78$, $p = 0.025$), reflecting a temporary low point followed by resumed upward momentum as restrictions lifted and vaccine access expanded.

The most dramatic change occurred in the Post-COVID period (2023–2024), where a substantial level increase ($\beta = 336.07$, p ¡ 0.001) signaled a structural elevation in crime counts. However, the post-phase trend remained flat ($p = 0.75$), suggesting stabilization at a higher crime baseline.

Monthly fixed effects (Table 1) confirmed expected seasonality, with significant winter declines (e.g., February, $\beta = -296.29$, p ¡ 0.001) and summer peaks (e.g., July, $\beta = 300.48$, p ¡ 0.001). These rhythms are consistent with long-established seasonal trends in urban crime.

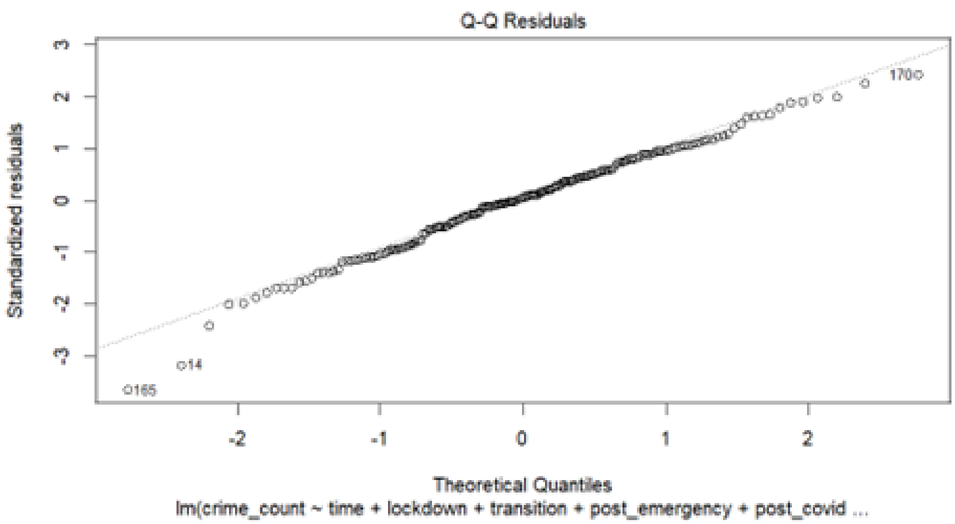

Figure 11: Q–Q plot of model residuals. This plot assesses the normality of residuals from the linear regression model. The residuals generally follow the expected normal distribution, aligning closely with the diagonal reference line. Deviations are visible in the lower tail, indicating the presence of a few outliers, which is to be expected in large datasets. Despite these extreme values, the overall distribution remains approximately normal, supporting the validity of inference for most model coefficients.

Table 3: Residual summary statistics.

Statistic	**Value**
Minimum	-398.82
1st Quartile (Q1)	-64.77
Median	6.30
3rd Quartile (Q3)	70.49
Maximum	266.11

Model validity is further supported by residual behavior. As shown in the Q–Q plot of residuals (Figure 11), the distribution is approximately normal with only modest tail deviations, suggesting no major violations of linear modeling assumptions. The residual summary statistics (Table 3) confirm reasonable dispersion, with most predictions falling within ±100 incidents of observed values. Together, these diagnostics reinforce the reliability of the ITSA model in capturing the broad temporal dynamics of crime across the pandemic timeline.

Table 4: Newey-West adjusted coefficient estimates. Significance levels: ∗∗∗ (p ¡ 0.001), ∗∗ (p ¡ 0.01), ∗ (p ¡ 0.05).

Predictor	**Estimate**	**Std. Error**	**t value**	**p-value**	**Significance**
(Intercept)	1767.58	55.82	31.66	¡0.001	***
time	-5.72	0.53	-10.87	¡0.001	***
lockdown	-169.16	36.82	-4.59	¡0.001	***
transition	-109.72	85.72	-1.28	0.202	
post_emergency	-193.66	79.66	-2.43	0.016	*
post_covid	336.07	68.10	4.93	¡0.001	***
time_since_lockdown	-57.42	21.27	-2.70	0.008	**
time_since_transition	4.23	6.66	0.64	0.526	
time_since_post_emergency	23.78	10.53	2.26	0.025	*
time_since_post_covid	-1.21	3.75	-0.32	0.748	
January	-87.97	16.60	-5.30	¡0.001	***
February	-296.29	33.78	-8.77	¡0.001	***
March	-120.40	30.06	-4.01	¡0.001	***
April	-59.56	28.61	-2.08	0.039	*
May	128.88	35.67	3.61	¡0.001	***
June	181.48	48.93	3.71	¡0.001	***
July	300.48	46.06	6.52	¡0.001	***
August	298.27	51.41	5.80	¡0.001	***
September	141.01	52.65	2.68	0.008	**
October	146.74	33.64	4.36	¡0.001	***
November	-4.46	30.72	-0.15	0.885	

5.2. Counterfactual Forecasting and COVID Impact

To further evaluate how crime trends may have differed in the absence of the COVID-19 pandemic, a counterfactual forecasting approach was applied. Using the pre-pandemic segment of the ITSA model (with all COVID-related terms removed), crime counts were predicted forward into the COVID-affected period under the assumption that no intervention or disruption occurred. These predicted values were then overlaid on observed monthly crime counts.

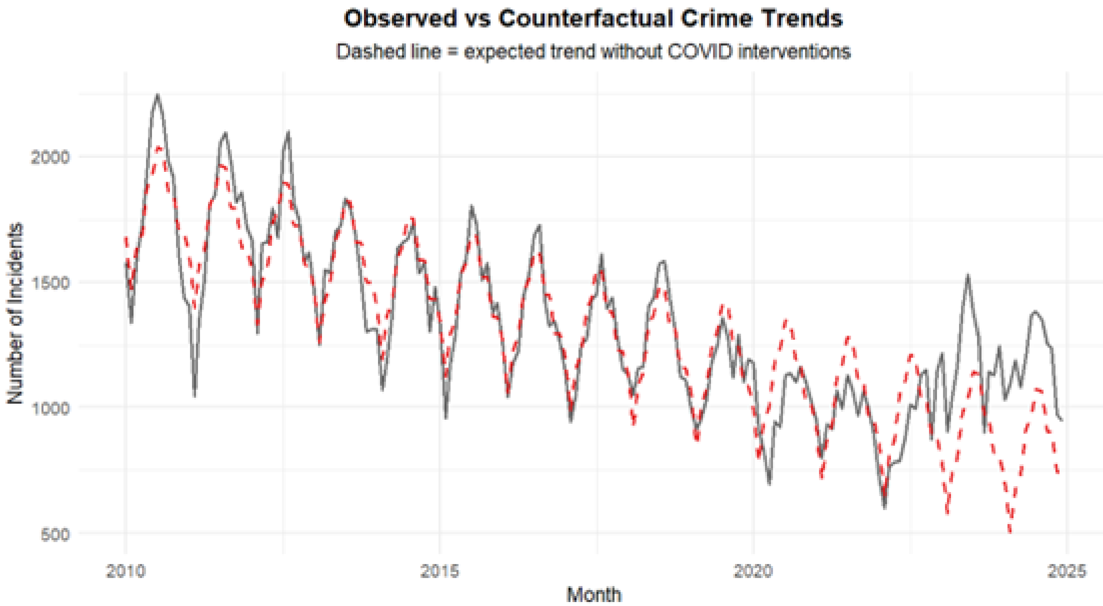

Figure 12: Counterfactual forecast vs. observed crime counts, 2010–2024. This figure displays monthly observed crime totals (solid line) alongside counterfactual predictions based on pre-COVID trends (dashed line). The model closely fits early pandemic behavior but increasingly underpredicts crime levels beginning in 2022, illustrating the lasting structural deviation associated with later pandemic phases.

The counterfactual model (Figure 11) closely tracks actual crime totals through early 2020 and remains relatively accurate during the initial phases of the pandemic, particularly through the Lockdown and Transition periods. Interestingly, the model anticipates typical seasonal increases during summer months, reflected in historical data, but these expected peaks did not materialize during the pandemic. This mismatch highlights how COVID-19 disrupted not only long-term trends but also predictable seasonal crime rhythms, likely due to restrictions on movement, altered social routines, and changes in public space usage.

The most substantial divergence between predicted and observed values emerges beginning in 2022, corresponding with the Post-Emergency phase. At this point, actual crime begins to rise significantly above the counterfactual trajectory, with the gap widening further into the post-COVID period (2023–2024). This deviation suggests that while early pandemic suppression effects were largely temporary and within the model's predictive range, longer-term shifts in structural or behavioral conditions—potentially tied to service disruptions, labor market shocks, or institutional adaptation—produced a sustained elevation in crime that would not have occurred under pre-pandemic trends.

These findings reinforce the conclusions drawn from the ITSA model: the pandemic initially suppressed crime through mobility restrictions and social disruption, but its longer-term impacts appear to have structurally altered urban crime patterns in Buffalo beyond what historical trends would predict.

5.3. Crime-Type-Specific ITSA Findings

To examine whether pandemic-related crime dynamics varied by offense type, separate ITSA models were estimated for five major categories: robbery, unauthorized use of a vehicle (UUV), breaking and entering, assault, and theft. The results reveal notable heterogeneity in how these offenses responded to the pandemic and its policy phases (Figure 13).

Robbery exhibited the clearest pattern of decline, with statistically significant decreases in both level and slope during the Lockdown and Post-Emergency periods. This suggests that reduced street activity and altered patterns of physical interaction likely constrained opportunities for person-to-person crimes. UUV, in contrast, showed a delayed response: its most significant decrease occurred during the Post-COVID period, possibly reflecting delayed policy or enforcement shifts, or a reduction in vehicle availability and access conditions during that time.

Breaking and entering dropped sharply during Lockdown, but this trend reversed during the Transition and Post-Emergency periods, where crime levels rebounded significantly. This U-shaped trajectory may reflect changes in residential routines, such as increasing time away from home, as normal activity resumed. Assault displayed a modest upward shift after 2020, but these changes were not statistically significant, highlighting the complexity of interpersonal violence trends and the possibility of offsetting factors like underreporting or delayed responses. Theft initially declined during the Lockdown phase and then stabilized at lower levels, with no significant changes detected in subsequent periods.

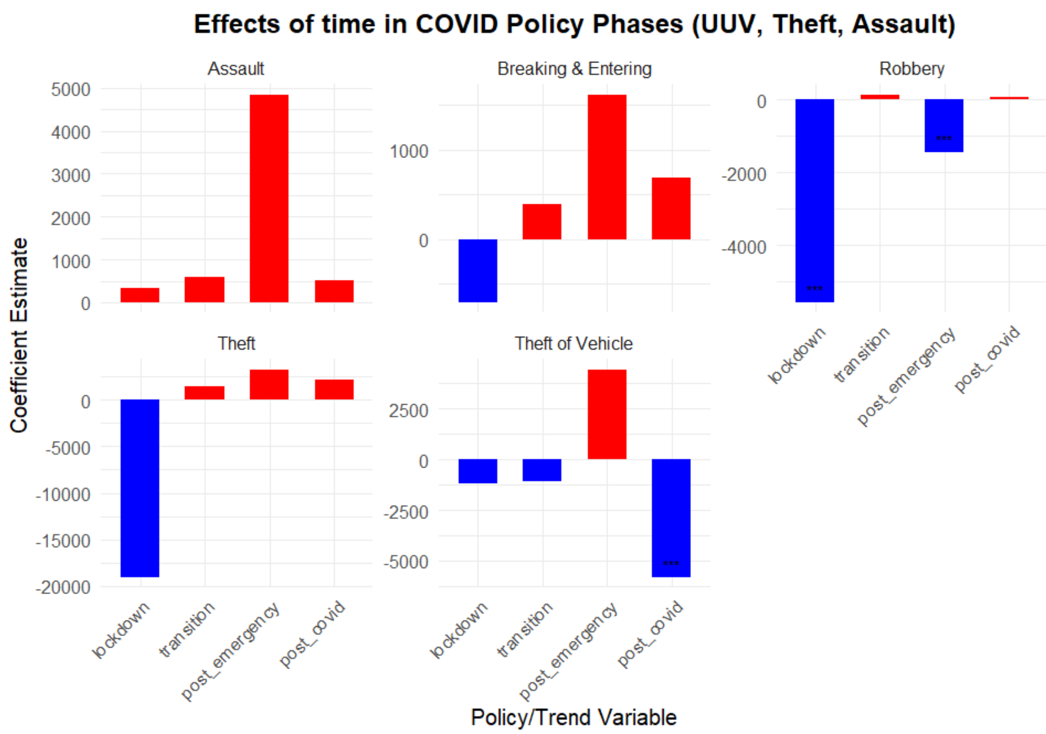

Figure 13: Estimated ITSA coefficients for COVID-era phases by offense type. This faceted bar plot compares the direction and relative magnitude of pandemic-period coefficient estimates across five major crime categories. Although few coefficients are statistically significant, this visualization highlights relative phase-specific effects and supports exploratory comparison of how different crimes may have responded to pandemic-related disruptions.

Overall, these disaggregated results support the hypothesis that different categories of crime were shaped by distinct behavioral, environmental, and structural conditions during the pandemic. Property crimes linked to opportunity structures rebounded as daily routines resumed, while personal crimes were more inconsistently affected by the changing social landscape. These findings underscore the value of offense-specific modeling in capturing the nuanced effects of pandemic-era disruption on urban crime.

5.4. Hotspot Detection and Local Spatial Autocorrelation

To statistically validate clusters of elevated crime, a Getis-Ord Gi* analysis was applied to census tract-level crime rates, adjusted for population using Empirical Bayes smoothing. The Gi* statistic measures local spatial autocorrelation, identifying tracts where high crime rates are not only elevated in isolation but are also spatially clustered, surrounded by other high-rate tracts. Tracts with z-scores greater than 2.58 were classified as statistically significant hotspots at the 99% confidence level, providing a formal test of clustering beyond simple descriptive mapping.

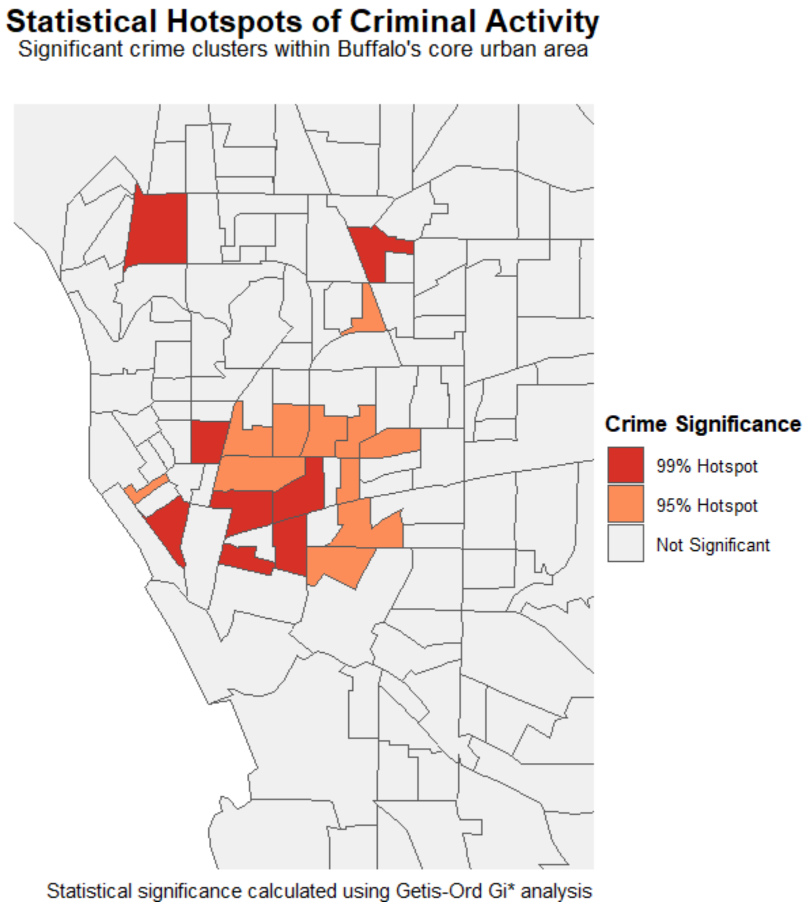

Figure 14: Buffalo census tracts classified by Gi hotspot status (99% confidence). This map displays statistically significant crime hotspots based on Getis-Ord Gi* analysis of tract-level crime rates. Tracts in red indicate clusters of elevated crime surrounded by similarly high-crime areas. Hotspots are primarily concentrated in Buffalo's East Side and parts of the Lower West Side and University Heights, confirming patterns of localized spatial clustering.

As shown in Figure 14, the Gi* analysis identified a clearly defined cluster of high-confidence hotspots concentrated in Buffalo's East Side, with additional clusters appearing in parts of the Lower West Side and near University Heights. These hotspots align with several of the highest-crime neighborhoods based on incident totals, including Broadway-Fillmore (n = 9,219), Masten Park (n = 5,463), and MLK Park (n = 4,012).

To visualize the spatial relationship between crime intensity and hotspot status, Figure 15 presents a faceted comparison of the Gi* hotspot map alongside the corresponding crime rate map. These side-by-side panels reinforce the finding that statistically significant hotspots tend to emerge in and around tracts with the highest density of crime. This alignment demonstrates that high crime counts alone are not sufficient for hotspot classification; rather, it is the spatial cohesion of those counts that produces significant clustering.

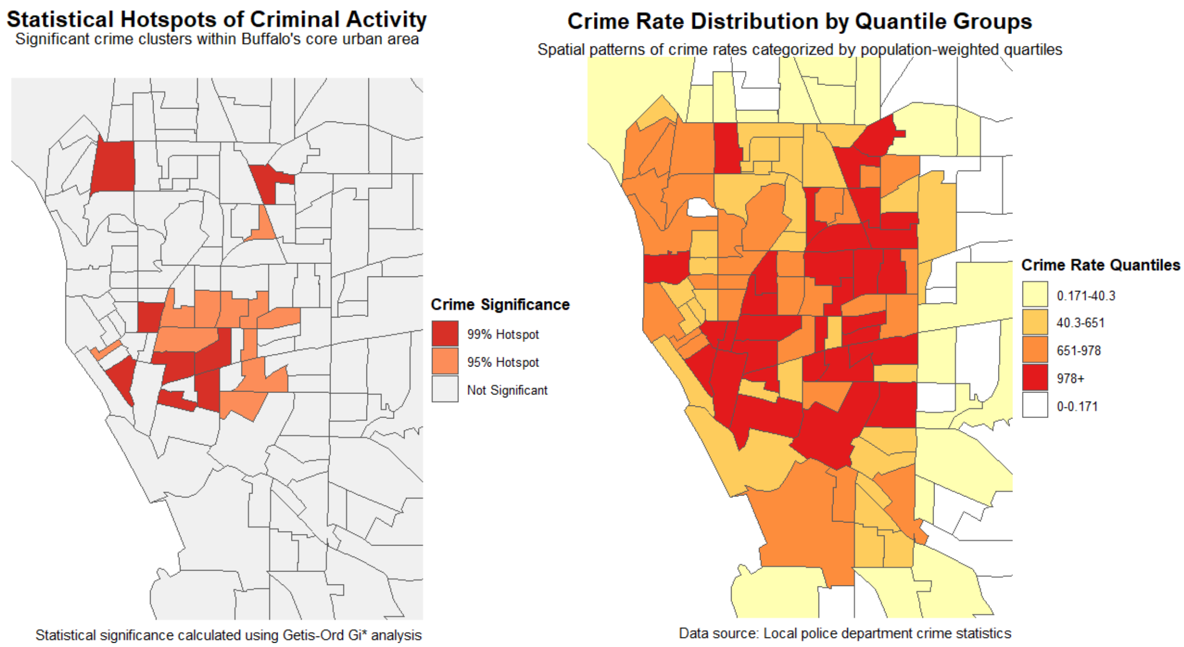

Figure 15: Faceted comparison of crime rate map and Gi hotspot map by census tract. This side-by-side visualization contrasts raw crime rates (left) with statistically significant hotspot classifications (right). While high-rate areas appear across the city, only areas with spatially adjacent high-crime tracts are identified as hotspots under the Gi* method. This comparison highlights the importance of spatial context in distinguishing structurally embedded crime concentrations from isolated high-incident tracts.

To assess whether crime patterns within identified hotspots deviated meaningfully from broader citywide trends, incident distributions were compared across hotspot and non-hotspot tracts. The analysis showed that hotspot tracts largely mirrored the temporal and categorical trends identified during exploratory analysis, including declines in crime during the early pandemic and rebounds in the post-COVID phase. However, some minor deviations were observed. On average, hotspot tracts exhibited slightly higher proportions of violent crimes, particularly assault and robbery, relative to non-hotspot areas. Conversely, theft-related incidents, including larceny and property-related offenses, comprised a somewhat smaller share of total crime in these high-risk areas. These differences, while modest, suggest that hotspot tracts may not only experience higher overall crime levels but may also bear a disproportionate burden of more serious or confrontational offenses. Nevertheless, the general consistency of trends across both groups reinforces the idea that the pandemic's influence on crime in Buffalo was citywide in timing, but spatially uneven in intensity.

6. Discussion

The results of this study provide compelling evidence that the COVID-19 pandemic influenced both the temporal dynamics and spatial distribution of crime in Buffalo, though not uniformly across crime types or neighborhoods. These findings contribute to the growing body of literature that seeks to understand the complex relationship between public health crises and urban crime patterns.

Temporal Trends and COVID-Era Disruptions

The interrupted time series results closely mirror national and international findings on the pandemic's short-term crime suppression effects. As reported in studies by Campedelli et al. [2020] and Meyer et al. [2022], crime declined sharply during early lockdowns, driven by disruptions to routine activity and increased guardianship. Our results confirm this pattern locally: crime in Buffalo dropped significantly during the Lockdown phase, remained suppressed into the Transition period, and began rebounding by 2022, ultimately stabilizing at a higher baseline in the post-COVID era. The counterfactual forecasting model further emphasized the structural nature of this change, showing that post-2022 crime levels exceeded what would be expected based on pre-pandemic trends. These deviations suggest that while some crime patterns initially conformed to routine activity theory, longer-term shifts may be attributable to institutional adaptation, economic displacement, or prolonged strain on public systems, consistent with the literature on social disorganization and structural vulnerability during crises.

Spatial Concentration and Localized Inequality

Spatially, this study confirms that Buffalo's crime remained highly concentrated throughout the pandemic, echoing long-standing research on crime concentration at place. Hotspot detection using the Getis-Ord Gi* method revealed that the most significant clusters were centered in the East Side and parts of the West Side—areas that align closely with historically marginalized neighborhoods. This pattern aligns with the localized insights of Zhang and Barr [2024], who highlighted the uneven effects of gentrification and disinvestment in Buffalo. Their study identified neighborhoods like Elmwood Bryant as experiencing redevelopment-driven changes, whereas high-crime neighborhoods like Broadway-Fillmore and Masten Park continue to face entrenched disadvantage.

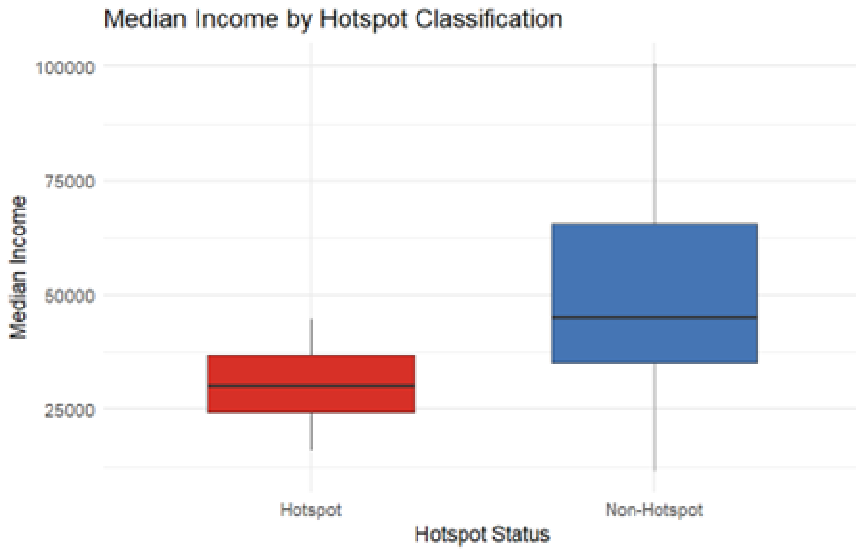

Figure 16: Box plot comparing median household income between hotspot and non-hotspot tracts. Hotspot tracts show significantly lower median incomes than non-hotspots, with a tighter range concentrated at the lower end of the distribution. This difference was statistically significant (p ¡ 0.001).

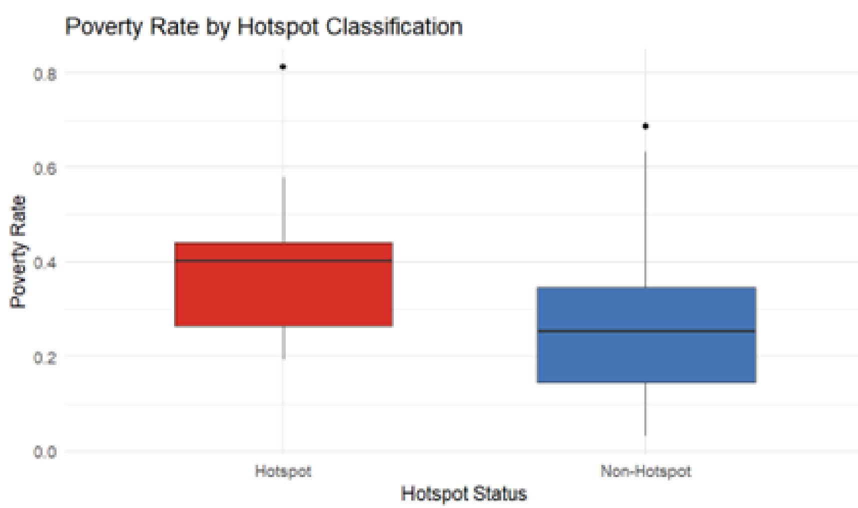

Figure 17: Box plot comparing poverty rates between hotspot and non-hotspot tracts. Hotspot areas exhibit notably higher poverty rates, with a wider distribution extending into more extreme values. This difference was statistically significant (p = 0.00135).

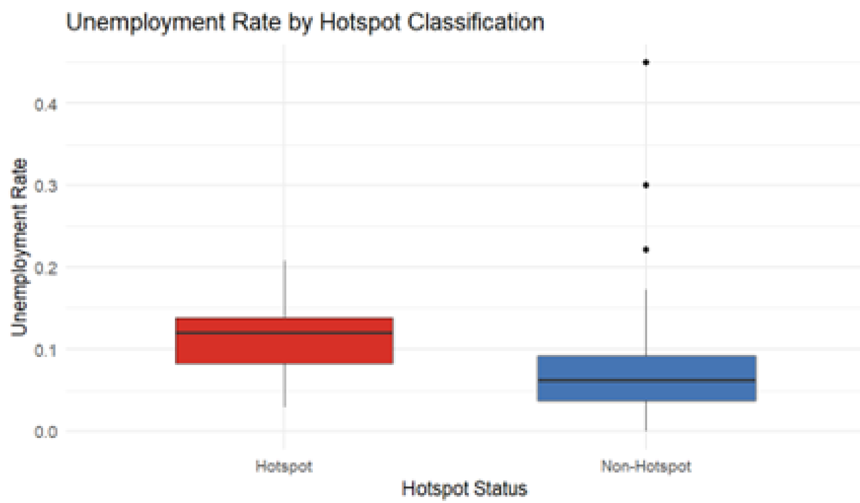

Figure 18: Box plot comparing unemployment rates between hotspot and non-hotspot tracts. Tracts identified as hotspots had significantly higher unemployment rates than non-hotspots, with greater variability in the upper quartile. This difference was statistically significant (p = 0.00669).

Statistical comparisons between hotspot and non-hotspot census tracts further reinforced the structural nature of crime concentration. As shown in Table 5, and visualized in Figures 16–18, hotspot tracts were significantly associated with lower median income (p ¡ 0.001), higher poverty rates (p = 0.00135), and elevated unemployment (p = 0.00669). These box plots highlight not only the median disparities but also the reduced interquartile range and more extreme lower-end values among hotspot tracts, suggesting deeper and more concentrated forms of disadvantage.

Table 5: Wilcoxon rank-sum test results comparing hotspot and non-hotspot tracts.

Variable	Group 1	Group 2	n1	n2	p-value
Median Income	Hotspot	Non-Hotspot	16	71	¡0.001
Poverty Rate	Hotspot	Non-Hotspot	16	71	0.00135
Unemployment Rate	Hotspot	Non-Hotspot	16	71	0.00669

Broader Structural Context and External Factors

Although this study isolates the pandemic as a major inflection point in Buffalo's crime trends, broader structural dynamics likely contributed to the post-COVID increases observed after 2022. The timing of these increases coincides with the expiration of eviction moratoriums, reductions in federal economic support, and heightened inflation—all of which introduced new forms of community strain. These economic stressors may have compounded the effects of the pandemic, particularly in neighborhoods already experiencing high unemployment and housing instability. The disruption of support systems such as schools, courts, and social services likely further weakened informal social controls. Seasonal effects also remain relevant: Buffalo's cold winters typically correspond with reduced street crime, a pattern confirmed in the ITSA's monthly effects. However, cities with more temperate climates may not exhibit the same seasonal suppression, suggesting that pandemic-era crime changes must be interpreted within both climatic and socioeconomic contexts.

Future Research Directions

Future research should extend the temporal modeling framework applied here to include tract-level time series analysis, enabling the detection of localized crime trajectory shifts within individual hotspots. Doing so would clarify whether specific neighborhoods exhibited unique rebound or suppression patterns during different phases of the pandemic. Additional integration of data on housing evictions, school closures, and neighborhood-level policing changes would also help clarify the mechanisms driving structural change in post-COVID crime dynamics. Finally, comparative studies across cities with varying climates, policing structures, and economic resilience would provide critical context for distinguishing local anomalies from broader national trends.

Implications for Policy and Future Emergency Response

These findings carry important implications for crime prevention and public safety planning in future public health or emergency contexts. The time series results suggest that while short-term suppression is achievable through widespread disruptions to routine activity, long-term crime control requires attention to structural conditions, particularly in high-risk neighborhoods. Spatial patterns reinforce the need for place-based interventions that address underlying socioeconomic vulnerabilities. Emergency response frameworks must go beyond enforcement and include equitable access to resources, social support, and community stabilization in areas most susceptible to compounding shocks.

Revisiting Research Questions and Hypotheses

This study set out to examine whether COVID-19 introduced significant changes in crime trends and whether these changes varied by crime type and geography. The results affirm the core hypotheses: pandemic-related shifts in crime were measurable, uneven across offense categories, and deeply conditioned by local spatial context. In particular, crime types linked to routine opportunity structures showed clearer pandemic-phase responses, while violent crimes and property offenses rebounded differently across time and place. The spatial consistency of Buffalo's hotspots, paired with their structural disadvantage, underscores the importance of integrating temporal modeling with neighborhood-level analysis in future urban criminological research.

7. Conclusion

This study used a combination of temporal modeling, spatial clustering, and socioeconomic analysis to investigate the impact of the COVID-19 pandemic on crime patterns in Buffalo, New York. Through interrupted time series analysis, the research documented clear phase-based shifts in crime rates—initial suppression during lockdown, a plateau through the transition period, and a marked increase in the post-pandemic era that exceeded pre-COVID trends. Disaggregating by offense type revealed that different crimes followed distinct trajectories, with person-based crimes and vehicle theft exhibiting delayed or prolonged responses, while opportunity-driven property crimes followed more immediate shifts. Spatial analysis using Getis-Ord Gi* statistics confirmed that crime remained concentrated in historically disadvantaged neighborhoods, and socioeconomic comparisons demonstrated significant disparities in income, poverty, and unemployment between hotspot and non-hotspot areas.

These findings have direct implications for both urban policy and emergency planning, reinforcing the idea that public safety during crises cannot be disentangled from long-standing social inequalities. They also underscore the value of integrating statistical modeling with spatial and socioeconomic data—a core tenet of applied data science. The project highlights how data-driven approaches can not only detect shifts in urban dynamics but also uncover the persistent structures that shape community vulnerability and resilience.

From a data science perspective, this research exemplifies the power of combining time series forecasting, spatial statistics, and public data integration to address real-world challenges. It demonstrates the utility of geographically weighted and temporally segmented methods in producing localized, actionable insights.

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