

PRESENTED BY: M.Z. Rifdy Ahamed

(S/17/305)

Outline

Introduction
Objectives of the Study
Literature Review
Description of the Dataset
Methodology
Results & Discussions
Conclusions
References

Introduction

- Crime analysis is the collecting and studying data about crimes to find patterns, understand offenders.
- The Covid-19 Pandemic started on December 31, 2019, in the Chinese city of Wuhan and rapidly developed into a global crisis.
- Global lockdowns and travel restrictions were implemented to combat the pandemic.
- This study analyzed how the COVID-19 lockdown affected crime in selected US cities.
- The most common crime types and hotspots between pre-COVID-19 and post-COVID-19 are compared and identified.

Introduction Cntd...

• The post-COVID-19 data was analyzed under the following three restriction reopen mapping phases for four cities:

Table 1: Four Cities' Reopening Mapping Phases of COVID-19 Restriction

City	Phase 1	Phase 2	Phase 3
Chicago	2020-03-03	2020-06-03	2021-03-02
	To	To	To
	2020-06-02	2021-03-01	2023-08-29
Dallas	2020-03-15	2020-05-29	2020-09-20
	To	To	To
	2020-05-28	2020-09-19	2023-08-29
Seattle	2020-05-28 To 2020-08-10	-	2020-08-11 To 2023-08-29
Phoenix	2020-03-31	2020-06-29	2020-09-03
	To	To	To
	2020-06-28	2020-09-02	2023-08-29

Objectives of the Study

Analyze crime rates in each city under the pre-COVID-19 and post-COVID-19.

Detect changes in crime types and hotspots over time.

Detect significant changes in crime patterns in selected cities between the two-time frames.

Investigate how crime patterns change during each phase of restriction in four cities.

Literature Review

- Lopez and Rosenfeld (2021) explored the influence of the COVID-19 pandemic on crime trends in U.S. cities.
 - > Provides a link between COVID-19 measures and crime.
 - ➤ It found that property crime and drug offenses went down, and motor vehicle theft increased.
- Avila et al. (2023) investigated how the global COVID-19 pandemic affected violent crime rates in Stockton, California.
 - This study identified statistically significant changes in the slope of violent crime rates due to COVID-19.
 - rape, robbery, and simple assault.

Literature Review Cntd...

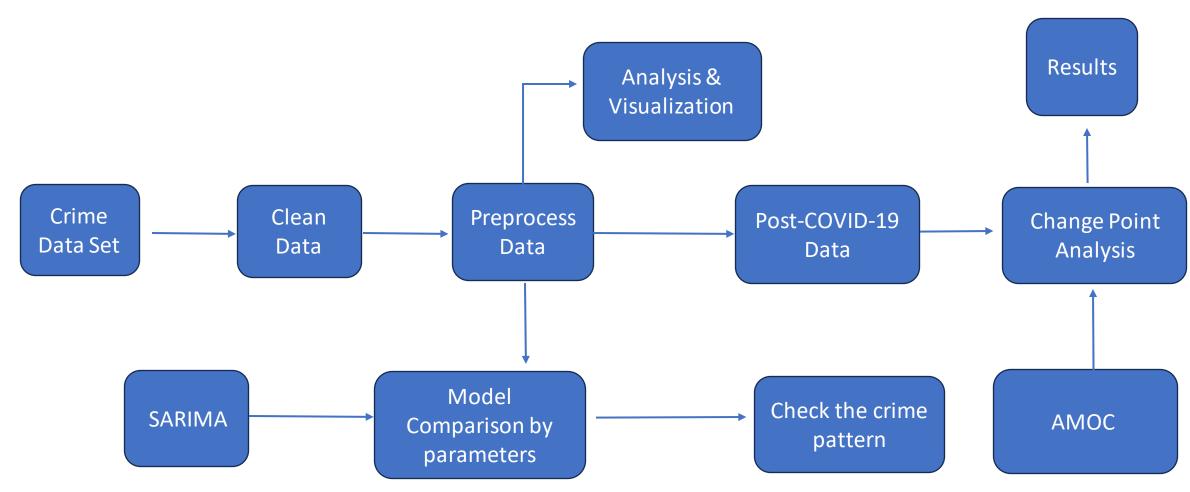
- Langton et al. (2021) examined how crime patterns changed in specific areas during the COVID-19 pandemic in England and Wales.
 - ➤ In most small areas, crime stayed about the same during the pandemic.
 - A few medium-sized areas, mainly city centers, show a significant impact on the overall crime pattern.

- Mohler et al. (2020) investigated the impact of social distancing measures during the COVID-19 pandemic on crime in Los Angeles and Indianapolis.
 - This study found that social distancing measures have some impact on crime and disorder, but the effects vary by crime type and location.

Description of the Dataset

- Data Sources: Online data portals of police departments in selected large cities in the USA.
- City-level weekly data from January 2016 to August 2023.
- Selected Cities: Chicago, Dallas, Seattle, and Phoenix.
- Timeframe:
 - 01 January 2016 31 December 2019 Pre-COVID-19
 - 01 January 2020 31 August 2023 Post-COVID-19

Methodology



Methodology Cntd...

- Change Point Analysis:
 - Detect the changes in mean daily crime counts
 - Single-changepoint technique (AMOC) method to detect the change points.
 - The penalty type used is MBIC, which is a default penalty function in R.
 - It is measure that balances goodness of fit and model complexity. Lower penalty values suggest more parsimonious models.
 - The test statistic being "normal" suggests that the algorithm uses a normal distribution as the basis for the test.

Results & Discussions

Table 2: Chicago Daily Crime Statistics for Pre and Post COVID-19 periods

City	Time Frame	Crime Type	Mean	SD	Min	Max	Ranking
,		THEFT	173.69336	28.778614	61	317	1
		BATTERY	136.11431	26.998781	78	247	2
		CRIMINAL DAMAGE	78.40041	15.990853	25	157	3
	Pre COVID	ASSAULT	54.11978	10.734978	24	88	4
	THE COVID	DECEPTIVE PRACTICE	53.26626	17.618433	12	202	5
		OTHER OFFENSE	46.96920	9.183428	20	87	6
		NARCOTICS	36.73990	11.470246	3	<mark>103</mark>	7
		BURGLARY	33.31485	9.592562	7	67	8
Chicago		MOTOR VEHICLE THEFT	28.49213	7.094816	8	<mark>66</mark>	9
		ROBBERY	28.41547	8.341792	6	63	10
	Post COVID	THEFT	129.67141	33.484915	4	<mark>337</mark>	<u>1</u>
		BATTERY	113.52994	23.844484	<mark>3</mark>	<mark>238</mark>	2
		CRIMINAL DAMAGE	72.51198	18.579797	2	343	3
		ASSAULT	55.40793	11.795850	1	91	4
	1 OSC CO VID	DECEPTIVE PRACTICE	46.85554	19.934070	2	162	5
		MOTOR VEHICLE THEFT	46.00225	27.167162	1	135	6
		OTHER OFFENSE	38.27994	9.110035	3	74	7
		WEAPONS VIOLATION	24.02172	8.848821	4	63	8
		ROBBERY	23.44045	8.291857	5	82	9
		BURGLARY	20.80524	19.273681	4	<mark>581</mark>	<mark>10</mark>

Table 3: Dallas Daily Crime Statistics for Pre and Post COVID-19 periods

City	 Time Frame	Crime Type	Mean	SD	Min	Max	Ranking
J		UNSPECIFIED CRIMES	278.021858	28.017207	<mark>181</mark>	<mark>401</mark>	1
		MISCELLANEOUS	66.045690	39.042317	1	206	2
		LARCENY/ THEFT OFFENSES	62.979287	22.458927	1	110	3
	Pre COVID	MOTOR VEHICLE THEFT	47.390459	15.418346	<mark>2</mark>	<mark>94</mark>	4
	PIE COVID	DESTRUCTION/ DAMAGE/ VANDALISM OF PROPERTY	27.037367	7.778686	1	56	5
		BURGLARY/ BREAKING & ENTERING	24.332458	8.214701	1	52	6
		ASSAULT OFFENSES	19.837044	6.776755	1	46	7
		ROBBERY	12.090992	5.177443	1	33	8
Dallas		PUBLIC INTOXICATION	11.179487	6.062675	1	38	9
		ALL OTHER OFFENSES	9.257014	4.149713	1	28	10
		MISCELLANEOUS	83.495892	14.962203	29	175	1
		LARCENY/ THEFT OFFENSES	79.310680	13.990568	26	129	2
		MOTOR VEHICLE THEFT	69.649739	23.405420	20	304	3
	Post COVID	DESTRUCTION/ DAMAGE/ VANDALISM OF PROPERTY	27.124720	7.198041	8	105	4
		ASSAULT OFFENSES	23.539208	6.931153	5	57	5
		BURGLARY/ BREAKING & ENTERING	19.265123	5.851353	5	44	6
		DRUG/ NARCOTIC VIOLATIONS	17.890800	7.411860	1	<mark>45</mark>	7
		ALL OTHER OFFENSES	11.994021	5.118780	1	92	8
		TRAFFIC VIOLATION - HAZARDOUS	9.664675	4.323472	1	<mark>32</mark>	9
		ROBBERY	7.652861	4.056029	1	27	10

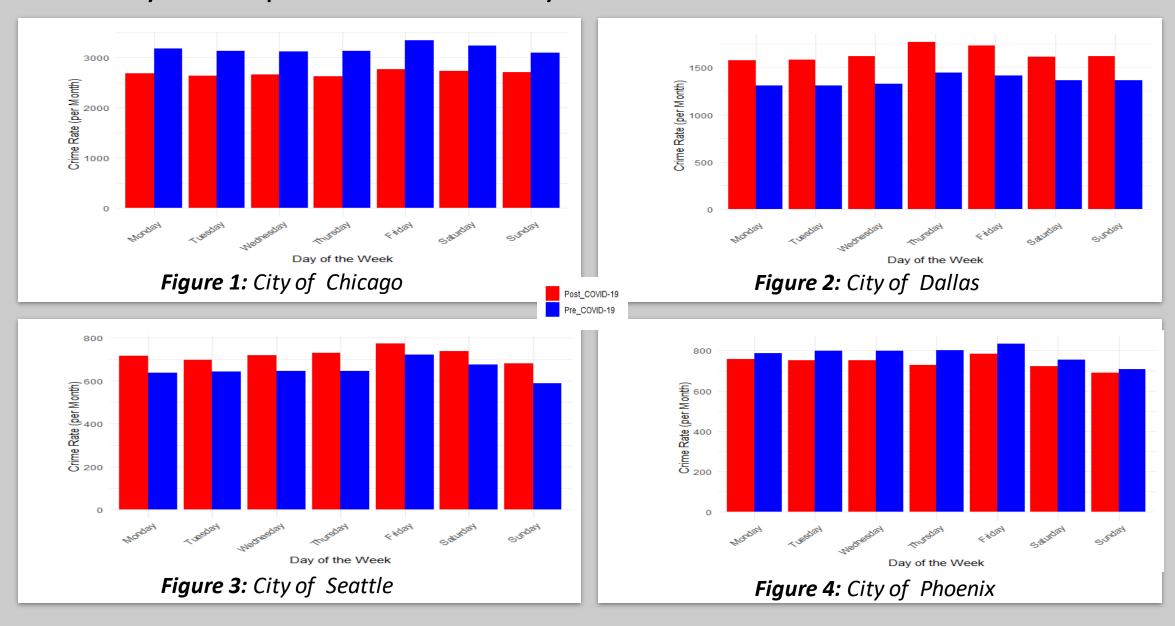
Table 4: Seattle Daily Crime Statistics for Pre and Post COVID-19 periods

City	Time Frame	Crime Type	Mean	SD	Min	Max	Ranking
J		LARCENY-THEFT	74.041058	11.518623	40	115	1
		ASSAULT OFFENSES	28.656934	6.535677	11	54	2
		BURGLARY/BREAKING&ENTERING	21.380474	5.363017	8	42	3
	Pre COVID	DESTRUCTION/DAMAGE/VANDALISM OF PROPERTY	17.889599	5.024655	4	42	4
		MOTOR VEHICLE THEFT	10.926095	3.719014	<mark>2</mark>	<mark>27</mark>	5
		FRAUD OFFENSES	10.297445	4.026060	1	<mark>29</mark>	6
		TRESPASS OF REAL PROPERTY	10.183562	3.918515	1	27	7
	Seattle	DRUG/NARCOTIC OFFENSES	5.890335	3.323078	1	<mark>25</mark>	8
Seattle		ROBBERY	4.443414	2.091689	1	13	9
		DRIVING UNDER THE INFLUENCE	3.780019	2.182233	1	16	10
		LARCENY-THEFT	72.206016	15.532443	14	149	1
		ASSAULT OFFENSES	29.844120	6.769965	11	55	2
		BURGLARY/BREAKING&ENTERING	26.411121	7.035078	8	71	3
	Post COVID	DESTRUCTION/DAMAGE/VANDALISM OF PROPERTY	19.348222	5.917235	6	54	4
		MOTOR VEHICLE THEFT	15.682771	5.471859	2	36	5
		FRAUD OFFENSES	15.494526	44.108231	1	542	6
		TRESPASS OF REAL PROPERTY	5.962420	3.201413	1	<mark>19</mark>	<mark>7</mark>
		ROBBERY	4.622921	2.299127	1	15	8
		DRIVING UNDER THE INFLUENCE	3.243590	1.822540	1	13	9
		STOLEN PROPERTY OFFENSES	2.330761	1.339983	1	9	10

Table 5: Phoenix Daily Crime Statistics for Pre and Post COVID-19 periods

City	Time Frame	Crime Type	Mean	SD	Min	Max	Ranking
J		LARCENY-THEFT	91.836413	13.2848122	42	143	1
		BURGLARY	28.120465	7.7582832	10	60	2
		MOTOR VEHICLE THEFTDAMAGE	18.930869	4.7033956	6	37	3
	Pre COVID	DRUG OFFENSE	15.346338	6.1670108	2	48	4
		AGGRAVATED ASSAULT	13.848734	4.4459902	2	31	5
		ROBBERY	7.633812	2.8207997	1	21	6
		RAPE	3.100453	2.9333281	1	54	7
		ARSON	1.776495	1.0448923	1	9	8
Phoenix		MURDER AND NON-NEGLIGENT MANSLAUGHTER	1.200903	0.4876753	1	4	9
		LARCENY-THEFT	87.328347	17.0387647	42	151	1
		MOTOR VEHICLE THEFT	20.706806	5.2864834	6	42	2
		AGGRAVATED ASSAULT	17.916978	4.8632331	3	37	3
	Post COVID	DRUG OFFENSE	16.673149	6.1168858	2	45	4
		BURGLARY	16.500374	5.0067507	4	<mark>39</mark>	5
		ROBBERY	6.263514	2.7138107	1	18	6
		RAPE	2.850993	2.0497497	1	33	7
		ARSON	2.452031	1.4192777	1	9	8
		MURDER AND NON-NEGLIGENT MANSLAUGHTER	1.307263	0.5989756	1	5	9

Weekly crime pattern of each city under the two time frames.



Friday Crime Peaks:

➤ All four cities have more crimes on Fridays in both pre- and post-COVID-19 times.

Pre vs. Post-COVID-19:

➤ Before COVID-19, Chicago and Phoenix had more crimes, but post-COVID-19, Dallas and Seattle's crime rates increased.

• Chicago's Consistent High Crime:

> Chicago consistently has a higher weekly crime rate compared to Dallas, Phoenix, and Seattle in both time frames.

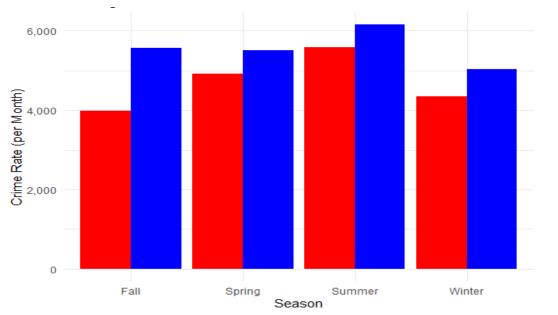


Figure 5: Seasonal Crime Rate City of Chicago

Post_COVID-19

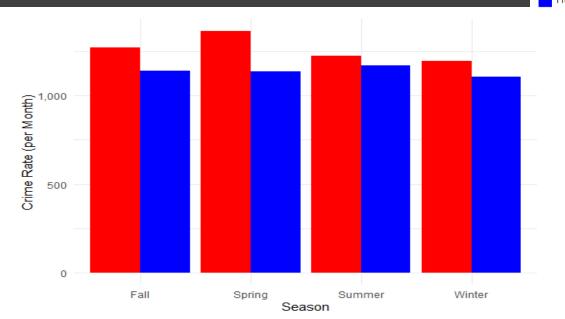


Figure 7: Seasonal Crime Rate City of Seattle

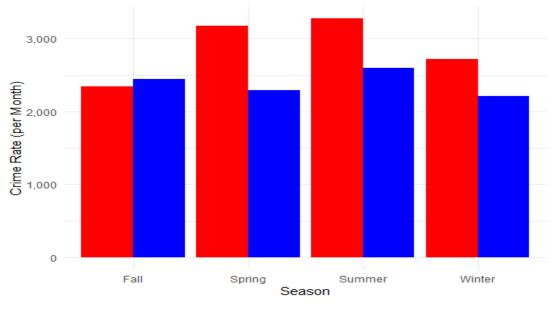


Figure 6: Seasonal Crime Rate City of Dallas

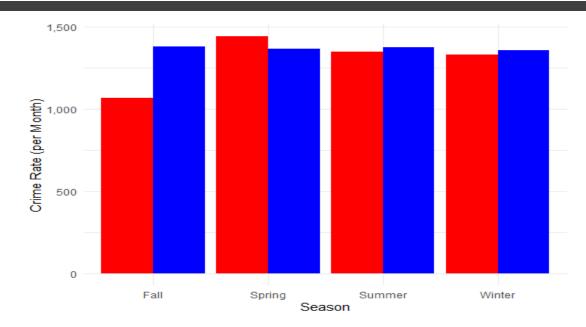


Figure 8: Seasonal Crime Rate City of Phoenix

Seasonal Crime Rates:

➤ Chicago consistently had a high crime rate throughout all seasons before COVID-19, while Dallas and Phoenix showed higher rates after COVID-19.

Summer Crime Peaks:

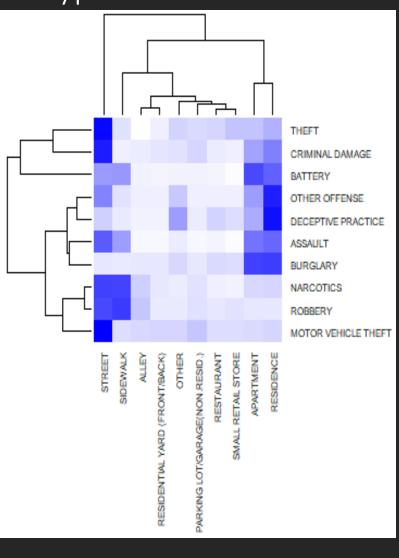
➤ Both Chicago and Dallas had elevated crime rates during the summer in both time frames

 Chicago, Seattle and Phoenix show similar crime rates in fall and spring precovid 19.

Seasonal Variations:

➤ Phoenix and Seattle had slightly higher crime rates in the spring. However, Chicago consistently showed higher seasonal crime rates compared to the other three cities.

 Relationships between crime types and location types.



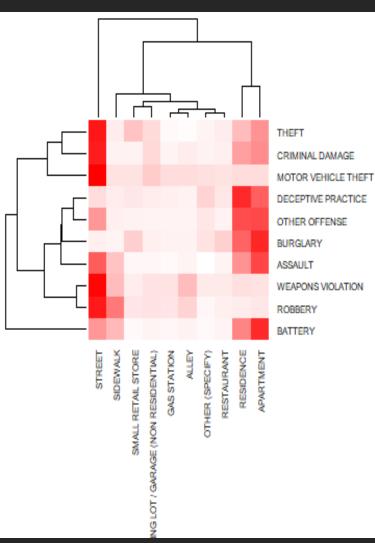


Figure 9: Chicago pre COVID-19

Figure 10: Chicago post COVID-19

• Street:

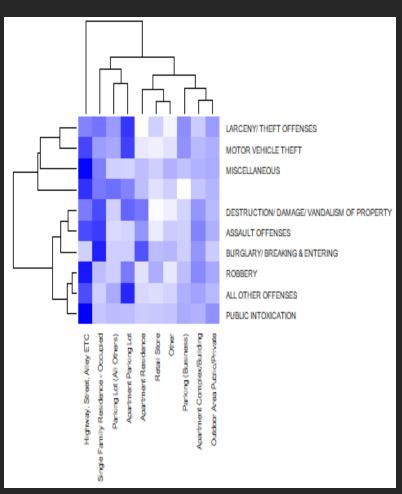
- ➤ Before COVID-19, high association with THEFT, CRIMINAL DAMAGE, MOTOR VEHICLE THEFT. Slightly higher association with NARCOTICS.
- ➤ Post-COVID-19 Strong correlation with THEFT, CRIMINAL DAMAGE, MOTOR VEHICLE THEFT, WEAPONS VIOLATION, and ROBBERY.

Apartment:

➤ BURGLARY and BATTERY have high associations in both time periods.

• Residence:

➤ Post-COVID-19 shows a lower number of highly associated crime types compared to pre-COVID-19.



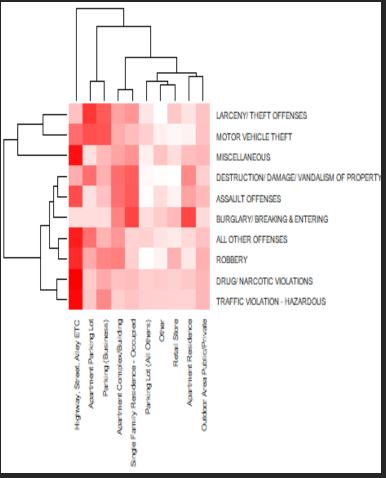
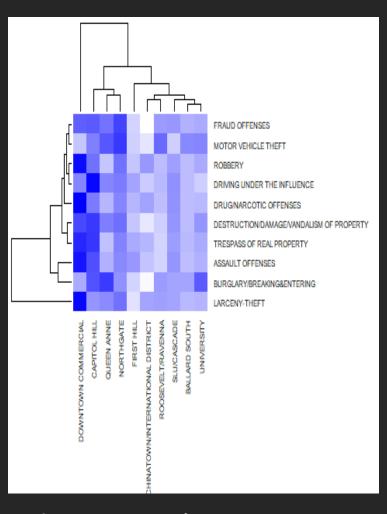


Figure 11: Dallas pre COVID-19

Figure 12: Dallas post COVID-19

Roadway Crimes:

- Before COVID-19, Dallas Highway, Street, and Alley highly associated with PUBLIC INTOXICATION and ROBBERY.
- ➤ Post-COVID-19, there's a slightly higher association with these crimes.
- Single Family Residence (Occupied):
 - ➤ Highly associated with BURGLARY/BREAKING & ENTERING in both pre and post-COVID-19 periods.
- Dallas shows fewer highly associated crime types in post-COVID-19 compared to pre-COVID-19.



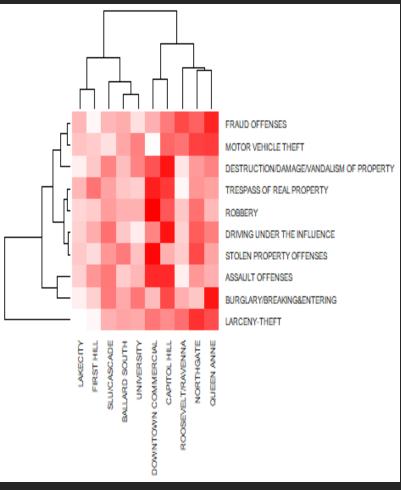


Figure 13: Seattle pre COVID-19

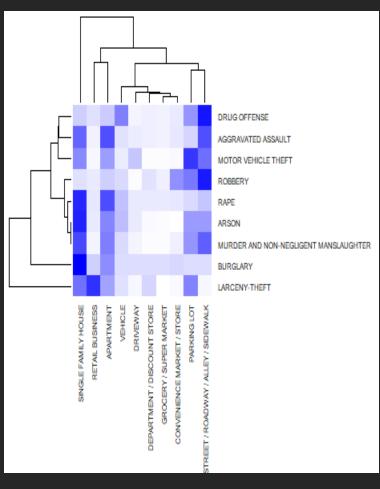
Figure 14: Seattle post COVID-19

Downtown Commercial Area:

- ➤ Before COVID-19 high association with LARCENY-THEFT, ASSAULT OFFENSES, DRUG/NARCOTIC OFFENSES.
- Post-COVID-19 Still highly associated with ASSAULT OFFENSES, STOLEN PROPERTY OFFENSES, TRESPASS ON REAL PROPERTY, and ROBBERY.

Capitol Hill:

- ➤ Before COVID-19 show Slightly more associated with DRIVING UNDER THE INFLUENCE.
- Post-COVID-19 sow high association with DRIVING UNDER THE INFLUENCE, ASSAULT OFFENSES, and DESTRUCTION/DAMAGE/VANDALISM OF PROPERTY.



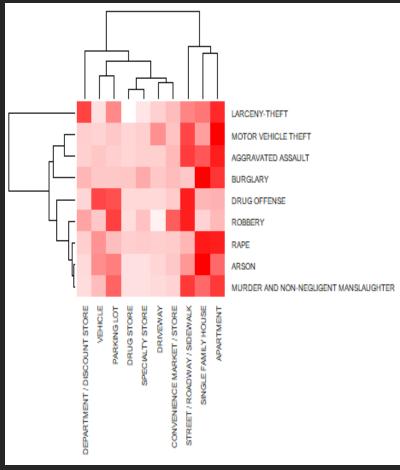


Figure 15: Phoenix pre COVID-19

Figure 16: Phoenix post COVID-19

1. Single Family Houses:

Highly associated with BURGLARY, ARSON, and RAPE in both time frames.

2. Roadway Crimes:

Streets and roadways highly associated with ROBBERY and DRUG OFFENSE in both time frames.

3. Apartments:

- ➤ Before COVID-19, Apartments had low associations with crime types.
- After COVID-19 High associations with MURDER, RAPE, BURGLARY, AGGRAVATED ASSAULT, MOTOR VEHICLE THEFT, and LARCENY-THEFT.
- 4. Single Family Houses show consistent associations in both time frames.

Time series pattern analysis

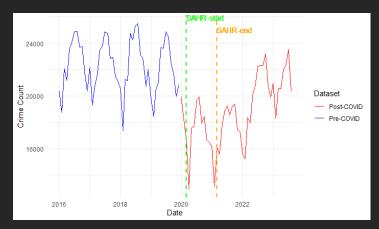


Figure 17: Chicago Crime Pattern



Figure 18: Dallas Crime Pattern

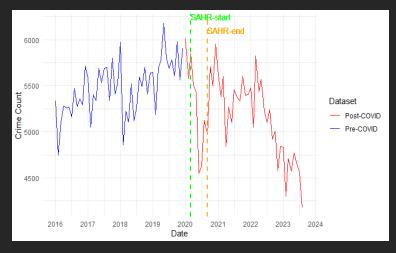


Figure 19: Phoenix Crime Pattern

Chicago Crime Pattern:

- Suggested best model for pre COVID-19: ARIMA(1,1,0)[12] model.
- Suggested best model for post COVID-19: ARIMA(0,1,0)(1,1,0)[12] model.

Dallas Crime Pattern:

- Suggested best model for pre COVID-19: ARIMA(0,1,0) model.
- Suggested best model for post COVID-19: ARIMA(0,1,1) model.

Phoenix Crime Pattern:

- Suggested best model for pre COVID-19: ARIMA(1,0,0)(1,1,0)[12] model.
- Suggested best model for post COVID-19: ARIMA(1,1,0)(1,0,0)[12] model.

 Analysis of crime patterns during each of the COVID-19 restriction mapping phases.

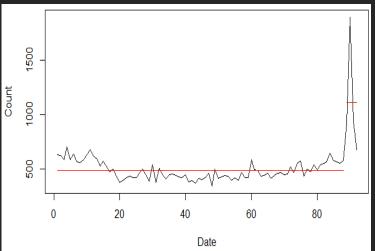


Figure 20: Chicago Phase 1

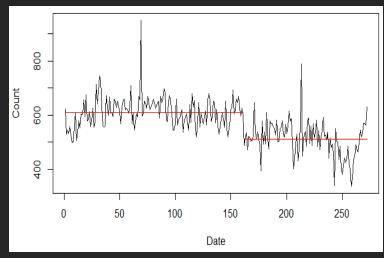


Figure 21: Chicago Phase 2

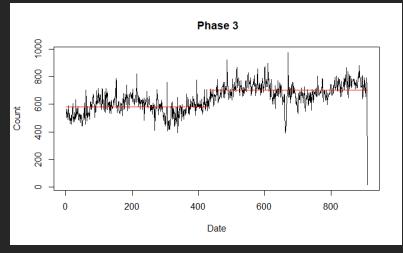
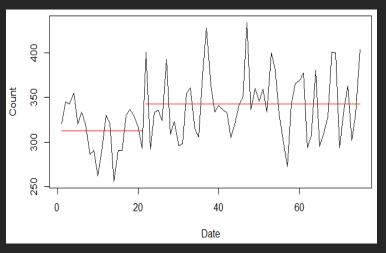


Figure 22: Chicago Phase 3

Chicago

Table 6: Summary statistics of change point analysis for Chicago

Phase Type	Phase 1	Phase 2	Phase 3
Changepoint Type	Change in mean	Change in mean	Change in mean
Method of analysis	AMOC	AMOC	AMOC
Test Statistic	Normal	Normal	Normal
Type of penalty : MBIC with a value	13.56537	16.81741	20.44033
Total number of days	91	271	910
Changepoint Locations	88	161	433
Changepoint Locations in Date format	May 3, 2020	November 11, 2020	May 10, 2022



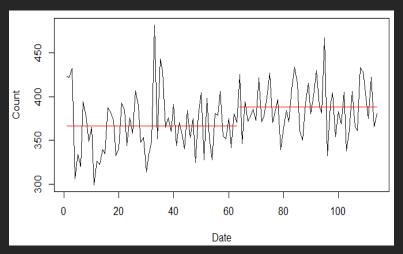


Figure 23: Dallas Phase 1

Figure 24: Chicago Phase 2

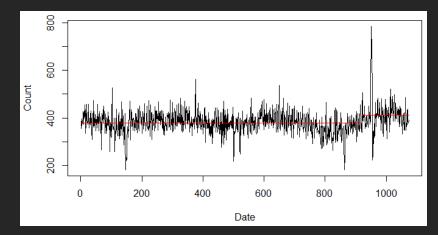
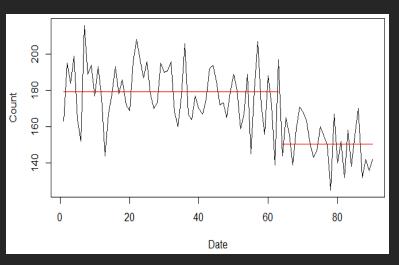


Figure 25: Dallas Phase 3

> Dallas

Table 7: Summary statistics of change point analysis for Dallas.

Phase Type	Phase 1	Phase 2	Phase 3
Changepoint Type	Change in mean	Change in mean	Change in mean
Method of analysis	AMOC	AMOC	AMOC
Test Statistic	Normal	Normal	Normal
Type of penalty : MBIC with a value	12.95246	14.2086	20.93744
Total number of days	74	113	1073
Changepoint Locations	21	63	921
Changepoint Locations in Date format	April 4, 2020	July 31, 2020	March 19, 2023



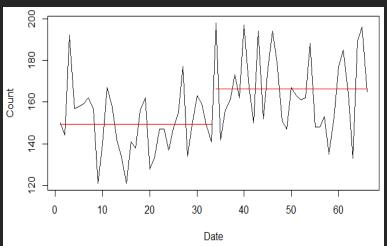


Figure 26: Phoenix Phase 1

Figure 27: Phoenix Phase 2

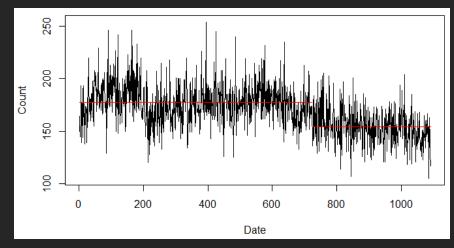


Figure 28: Phoenix Phase 3

> Phoenix

Table 8: Summary statistics of change point analysis for Phoenix.

Phase Type	Phase 1	Phase 2	Phase 3
Changepoint Type	Change in mean	Change in mean	Change in mean
Method of analysis	AMOC	AMOC	AMOC
Test Statistic	Normal	Normal	Normal
Type of penalty : MBIC with a value	13.49943	12.56896	20.98455
Total number of days	89	65	1090
Changepoint Locations	63	33	723
Changepoint Locations in Date format	June 2, 2020	August 1, 2020	August 29, 2022

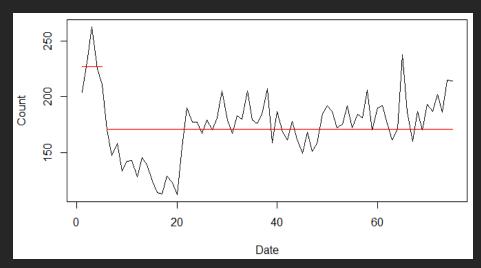


Figure 29: Seattle Phase 1

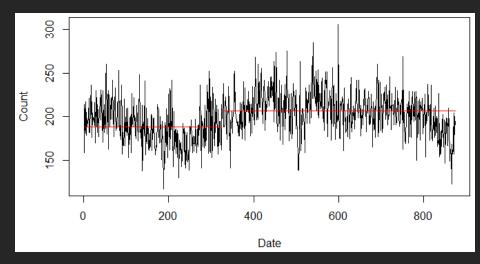


Figure 30: Seattle Phase 3

> Seattle

Table 9: Summary statistics of change point analysis for Seattle.

Phase Type	Phase 1	Phase 3
Changepoint Type	Change in mean	Change in mean
Method of analysis	AMOC	AMOC
Test Statistic	Normal	Normal
Type of penalty: MBIC with a value	12.95246	20.31924
Total number of days	74	1114
Changepoint Locations	5	324
Changepoint Locations in Date format	June 6, 2020	July 1, 2021

Conclusions

- The findings of this study contribute toward a better understanding of changes in crime patterns before and after COVID-19 in Chicago, Dallas, Phoenix, and Seattle.
- The overall findings suggest that:
 - > The summers are dangerous in Chicago and Dallas.
 - > Friday is the most risky day in all four cities.
 - ➤ Most of the crimes are associated with
 - streets, apartments, and residences at both time frames in four cities.
- A rapid drop occurred at the beginning of the COVID-19 restriction period.
- After most of the restrictions were lifted, the patterns went back to their usual patterns.
- phse1 showed significant changes in crimes compared with the other two phases.

References

- Lopez, E. and Rosenfeld, R. (2021). Crime, quarantine, and the us coronavirus pandemic. Criminology & Public Policy, 20(3):401–422.
- Avila, D., Gao, H., Randol, B., and Chintakrindi, S. (2023). Covid-19: Examining the impact of the global pandemic on violent crime rates in the central valley of california. International Journal, 12:43.
- Langton, S., Dixon, A., and Farrell, G. (2021). Small area variation in crime effects of covid-19 policies in england and wales. Journal of Criminal Justice, 75:101830.
- Mohler, G., Bertozzi, A. L., Carter, J., Short, M. B., Sledge, D., Tita, G. E., Uchida, C. D., and Brantingham, P. J. (2020). Impact of social distancing during covid-19 pandemic on crime in los angeles and indianapolis. Journal of criminal justice, 68:101692.



Thank you!