Annual Report

Reporting Period July 1, 2024- June 30, 2025

Contents

Executive Summary

The Ohio General's Center for Justice Research (CJR) at Bowling Green State University goal is to inform criminal justice policy through science, the CJR funds original research that is designed to answer key questions about criminal justice, justice administration and justice policy in Ohio. The Center for Justice Research's motto – "Science Informing Policy" – directly reflects its purpose.

The Ohio Attorney General's Center for Justice Research's mission: At the Center for Justice Research, we believe in the power of science to inform policy. Our mission is to promote data-driven, effective, and fair policy solutions to Ohio's most pressing criminal issues. Collaborating with scientists and scholars across Ohio and the United States, we conduct innovative research and share our findings with criminal justice practitioners, academia, and the public. During this reporting period the mission and goals of the Center for Justice Research have been supported by:

- Enhanced analytical capacity by bringing on an additional graduate assistant in Data Science to continue the development of predictive modeling and mapping tools
- Brought an undergraduate research assistant to the team to improve the efficiency of data cleaning and literature search processes.
- Coordinated with agencies across Ohio, including the Toledo Police Department and the Ohio Incident-Based Reporting System housed in the Offices of Criminal Justice Services, as well as with agencies outside of Ohio, including Michigan Incident Crime Reporting, Michigan State Police, and Indiana State Police, to access and obtain data.
- Completed the *Permit or Permitless Carry: A Longitudinal Study Comparing Ohio and Michigan Firearm Crime Incidents* covering years June 2020-June 2024.
- Presented research on both the *Residential Instability, Calls for Service, and Crime in Toledo, Ohio: A 10-Year Lookback* study and the *Permitless Carry and Crime Trends: A Tale of Two Rivals - Ohio vs. Michigan* analyses at the Academy of Criminal Justice Sciences annual meeting in Denver, CO.

Memorandum of Understanding

The Center for Justice Research was established during the previous reporting period with an effective date of November 1, 2021, through a Memorandum of Understanding between Bowling Green State University and the Ohio Attorney General's office.

Projects

Project 1: Residential Mobility and Crime in Ohio Project

During the previous fiscal year, two reports were submitted for the first CJR-funded project, examining the impact of residential instability on crime and calls for service across 92 census tracts in Toledo. The study found that residential instability significantly influenced crime and service call patterns both between and within tracts, offering insights for early crime prediction and community-police collaboration.

Based on the findings of the Toledo study, a replication analysis was conducted using data from the city of Dayton, Ohio. The purpose of this study was to assess if the 35 tracts within Dayton's city limits exhibited similar patterns between residential instability and calls for service/crime incidents. Data used in this project included 2012-2019 calls for service and crime incident records from the Dayton Police Department. As in the Toledo study, residential instability was measured using vacancy information obtained from the Department of Housing and Urban Development, along with data on renter occupied housing and geographic mobility sourced from the U.S. Census Bureau and the American Community Survey (ACS) 5-Year Estimates. Additional demographic variables at the census tract level were also drawn from the Census Bureau and the ACS.

Due to the smaller sample size in Dayton – 35 census tracts as opposed to Toledo's 92 a longitudinal (i.e., vector autoregressive[1]) analysis could not be employed. The results of standard multivariate regression[2] indicated that the total population of tracts was frequently a significant predictor of both calls for service and crime incidents. In some cases, higher rates of female-headed households and lack of high school completion were also positively associated with calls for service and/or crime. The rate of vacant residences was significantly correlated with Part 1 property-related calls for service in 2014. However, no other residential instability variables were significantly associated with crime incidents and calls for service.

Overall, the findings for Dayton suggest that the smaller sample size may have limited the ability to detect the relationships observed in the Toledo study. Further examination of our regression model indicated that a minimum of 64 census tracts would be necessary to reliably detect these associations. Considering this information, the CJR team has initiated a new replication study using data from Cincinnati, whose 89 census tracts should provide an adequate sample size to evaluate whether the findings in Toledo are generalizable to other cities in Ohio.

For both Toledo and Dayton, predictive modeling was applied to the collected data. The Prophet model was used for its ability to detect patterns across time. In Toledo, the data were

[1] A VAR model is a multivariate time series model that estimates relationships between multiple variables measured at consecutive points in time.
[2] Multivariate regression is a statistical method used for examining the relationships between one dependent variable and one or more independent variables.

aggregated at the city level, as tract totals were too small for accurate predictions to be made. In Dayton, crimes counts were aggregated at the police beat level, which is larger than the census tract but smaller than the whole city. Graphs from 2010 to 2025 in Toledo and 2012 to 2019 in Dayton were created for six crime categories, revealing long-term trends as well as seasonal patterns which recurred over time. Visualizations were created to illustrate trends and future projections. These included both time series plots, which spanned the entire study period, and decomposition plots, which showed trends at weekly and monthly levels. Key findings in Toledo showed an inverse relationship between Part 1 and 2 personal crime categories and a steady decline in property crimes. The model showed abrupt changes in the patterns of public order and drug crimes around 2020, which exposed some limitations of predictive utility of the model. The Dayton models mirrored Toledo's crime trends, with negative correlations between Part 1 and 2 crime categories, as well as declining property crimes.

Future project efforts include replication studies in Cincinnati and Cleveland, continued predictive modeling and data mapping, and ongoing data collection to examine how residential instability and other community factors affect crime over time.

Period of performance 01/25/2023-06/07/2024

Project 2: Constitutional Carry

In a final report submitted during the previous fiscal year, the CJR examined the impact of Ohio's permitless carry law (enacted June 13, 2022) on firearm-related crime across Ohio's eight largest cities. The study found an overall decrease in such incidents—particularly in Akron, Columbus, and Toledo—though slight increases occurred in Cincinnati and Dayton. The law appeared to have no significant effect on firearm-related injuries or deaths among law enforcement.

During the current fiscal year, the CJR built on this work by conducting a comparison study of firearm-related incidents between Ohio and Michigan. Michigan was selected due to its geographical proximity to Ohio and its permit requirements for concealed carry of a firearm, which differs from Ohio's (i.e., Michigan requires a concealed carry permit where Ohio does not). Data used in this comparison study included crime incidents involving a firearm in eight major Ohio cities – Akron, Canton, Cleveland, Cincinnati, Columbus, Dayton, Parma, and Toledo – and eight Michigan cities – Dearborn, Detroit, Flint, Grand Rapids, Kalamazoo, Lansing, Sterling Heights, and Warren. The analysis covered the period from June 2020-June 2024, utilizing data from the Ohio Incident-Based Reporting System (OIBRS) and the Michigan Incident Crime Reporting (MICR) system.

Mann-Kendall trend[3] tests and an independent samples t-tests[4] were conducted to assess changes in firearm-related crime incidents in both states. In Ohio, the analyses were run twice:

[3] The Mann-Kendall tests for the significance of consistently increasing or decreasing trends in data.
[4] Independent samples t-tests indicates whether or not there were significant differences pre- and post-PCL.

first using data from all eight cities between June 2020 and December 2023, and again from June 2020 to June 2024, excluding Columbus[5]. The Mann-Kendall trend test revealed declining trends in firearm-related incidents in each city and across all cities combined for both timeframes. In the initial analysis (i.e., June 2020-December 2023) that included Columbus, all cities displayed downward trends that were not statistically significant except Akron, Dayton, and Parma. When 2024 data were included for seven of the eight cities (all but Columbus), five of the cities exhibited significant declines. Akron and Dayton incidents decreased but were not statistically significant. In Michigan, the Mann-Kendall test also indicated significant downward trends in Detroit, Lansing, Dearborn, Kalamazoo, and the combined dataset. However, Sterling Heights experienced a statistically significant increase in firearm-related incidents over the study period.

The independent samples t-test for Ohio (June 2020–December 2023) showed significant variation in firearm-related crime rates across all cities and in each individual city, apart from Dayton. When the analysis was extended to include data through June 2024 (excluding Columbus), significant differences remained for all cities combined and each city independently except Akron and Dayton. For Michigan, the t-test results revealed significant variation in firearm-related incidents in Detroit, Sterling Heights, Lansing, Dearborn, Kalamazoo, and across all cities combined.

Future project efforts include extending the study's timeframe, continuing data collection and analyses for the cities of interest, as well as adding additional cities to the study's sample to evaluate how the PCL may influence crime incidents across various locations.

Period of performance: 07/11/2023-10/30/2023

For more details about these projects, see Appendix B.

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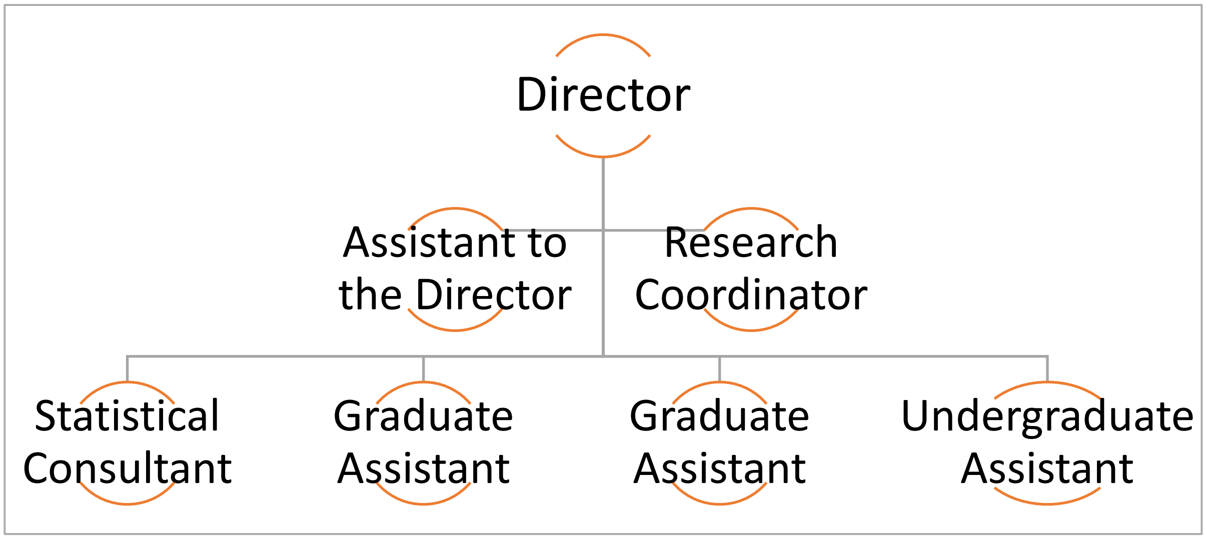
[5] Data from the Columbus Police Department is available through OIBRS only up to December 2023, so complete analysis of all eight cities from June 2020 to June 2024 was not possible.

Center Personnel

Below is the organizational chart for the CJR. During this fiscal year, we added a new position to the team, which was an undergraduate assistant. In addition, we were able to recruit a graduate assistant from the Master's program in Data Science to assist us with the mapping and predictive modeling elements to complement our research in visual form. The [BGSU webpage hosting the CJR] is updated with the current team members.

Organizational Chart for the Center for Justice Research



Center for Justice Research personnel consist of:

- Director, Dr. Melissa Burek
- Assistant to the Director, Nicole Pedraza
- Research Coordinator, Stephanie DeCroix
- Statistical Consultant, Dr. Eric Cooke
- Graduate Assistants
    - Jaryt Salvo (January 2024-present)
    - Emily Massie (August 2024-May 2025)
- Undergraduate Assistant
    - Aiden Kelly (February 2025-present)

Presentations and Future Publications

ACJS Panel and Poster Presentations

During the reporting period of July 1, 2024- June 30, 2025, we presented a poster depicting findings from the Permitless Carry project (see Appendix A) at the Academy of Criminal Justice Sciences (ACJS) annual meeting in March in Denver, CO. In addition, during this conference members of the CJR team participated in a panel presentation titled *Transforming Communities: The Influence of Residential Dynamics, Social Interventions, and Predictive Analysis on Crime Prevention*, speaking about their work on the Residential Instability project. The slide decks of which can be found in Appendix A.

Future Publications

The CJR team would like to reach broader audiences, including the more traditional academic journal readers. Currently, a manuscript focusing on the predictive models on crime in Toledo is underway. The CJR hopes to have a completed manuscript to submit for publication by the end of this summer. In addition, we are putting together a manuscript on the comparative analysis of Ohio and Michigan for the Permitless Carry project. Other publication ideas include a second manuscript focusing on residential instability measures and calls for service as related to crime in Toledo and on findings from the replication studies using data from Dayton and Cincinnati.

Collaborations and Communications

During the July 1, 2024-June 30, 2025, reporting period, the CJR collaborated with a variety of criminal justice agencies and organizations across Ohio. Notable partnerships included the Toledo Police Department's Intelligence and Special Investigations Bureau and the Ohio Incident-Based Reporting System. Through these collaborations, the CJR obtained essential data such as calls for service and crime incident data for Toledo and the numbers of crimes involving firearms in Ohio's largest/larger cities.

Beyond Ohio, our collaborations with researchers at Northeastern University and the University of Central Florida resulted in organizing a panel presentation at the ACJS Annual Meeting in Denver, CO. This opportunity allowed the CJR team to share our research with a broader academic and practitioner audience. Through our correspondence with the state police agencies in Michigan, Indiana, Pennsylvania, and Illinois, the CJR was able to obtain data which made possible the comparison study of firearm incidents in Ohio and Michigan. Collaboration with these agencies allowed the CJR to gain insight into how they function and allowed the CJR to successfully complete the projects at hand.

Continued communication with Ohio-based agencies and organizations, as well as those outside our own state, is expected to enhance the scope and impact of future research efforts conducted by the CJR. Official CJR websites have been continuously updated during this reporting period, which provides information on the CJR's mission, team members, press, and research activities.

Center for Justice Research Webpages

1. Main
2. Research and Reports
3. About Us
4. Press
5. Attorney General Dave Yost Center for Justice Research

Center for Justice Research Costs

Total expenditures to operate the Center for Justice Research for the reporting period July 1, 2024 to June 30, 2025 was $104,407.60. A breakdown of expenditures is below.

Dates: July 01, 2024, to June 30, 2025

Operation costs

Personnel and Fringes:	$101,941.21
Travel:	$2247.22
Supply:	$219.17

Amount expended during reporting period: $104,407.60

Indirect Costs $9,577.29

Fiscal Year 2025 Summary: Costs

Total expenditures: $113,984.89

Appendix A

Conference Presentations

Permitless Carry and Crime Trends: A Tale of Two Rivals - Ohio vs. Michigan*

Stephanie DeCroix, MSCJ, Julia Bell, MSCJ, Melissa W. Burek, Ph.D., & Eric M. Cooke, Ph.D.
Center for Justice Research at Bowling Green State University

Abstract

In the past decade, almost two dozen states have passed permitless or constitutional carry laws, allowing citizens to carry a concealed handgun without a permit. As one of those states, Ohio implemented its own such law in mid-2022. Its neighbor to the north, Michigan, however, prohibits concealed carrying of a firearm without a license. This study analyzed firearm-related crime incidents in Ohio's eight largest cities and compared them to similar cities in Michigan before and after Ohio's law took effect, to see if the change in legislation was associated with any differences in crime trends.

Background

- Mixed results on the true impact of permitless carry, and like laws, on crime and public safety.
- More lenient carry laws are associated with higher rates of fatal and non-fatal officer and citizen shootings.
  - Average of 12.9% increase in the rate of officer involved shootings.
- Impact on police:
  - Increased perceived threat of danger and suicide-by-cop incidents.
  - Decreased police-community relations and crime-suppressing police operations.

Method

Sample
- 1 June 2021 – 30 June 2023
- Ohio Incident-Based Reporting System (OIBRS) data for:
  - Columbus, Cleveland, Cincinnati, Toledo, Akron, Dayton, Parma, and Canton
- Michigan Incident Crime Reporting (MICR) data for:
  - Detroit, Grand Rapids, Warren, Sterling Heights, Lansing, Dearborn, Flint, Kalamazoo
- Crime incidents involving a firearm

Analysis
- Independent Samples T-Test
- Mann-Kendall Trend Test (MK)

Limitations
- Generalizability
- Time period
- Crime incident data provided by different sources: Ohio Incident-Based Reporting System (OIBRS), Michigan Incident Crime Reporting (MICR).

*Funded by The Ohio Attorney General Dave Yost,
Center for Justice Research at Bowling Green State University

Figure 1. Ohio Incidents Involving a Firearm per 1,000 Persons

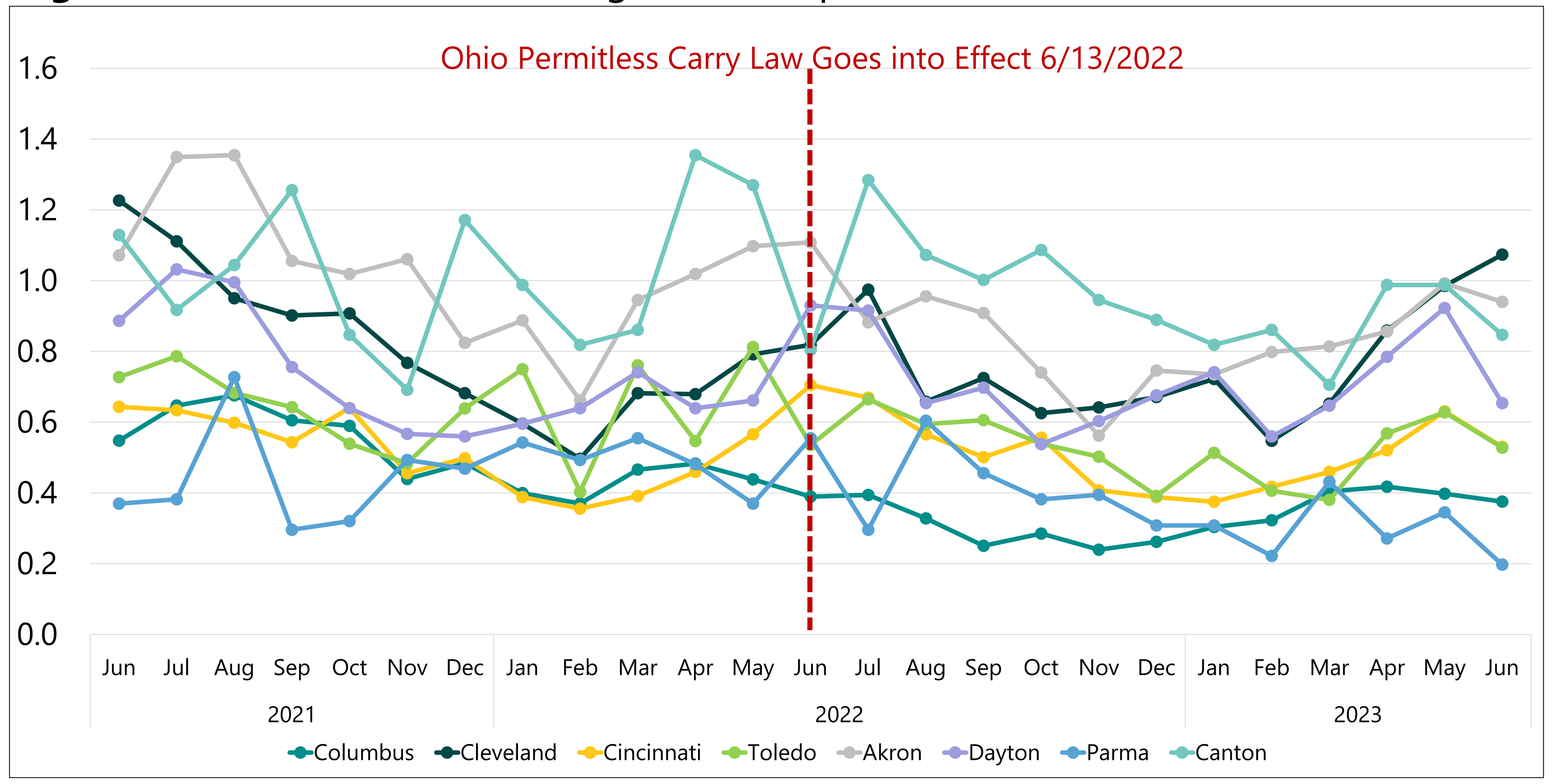


Figure 2. Michigan Incidents Involving a Firearm per 1,000 Persons

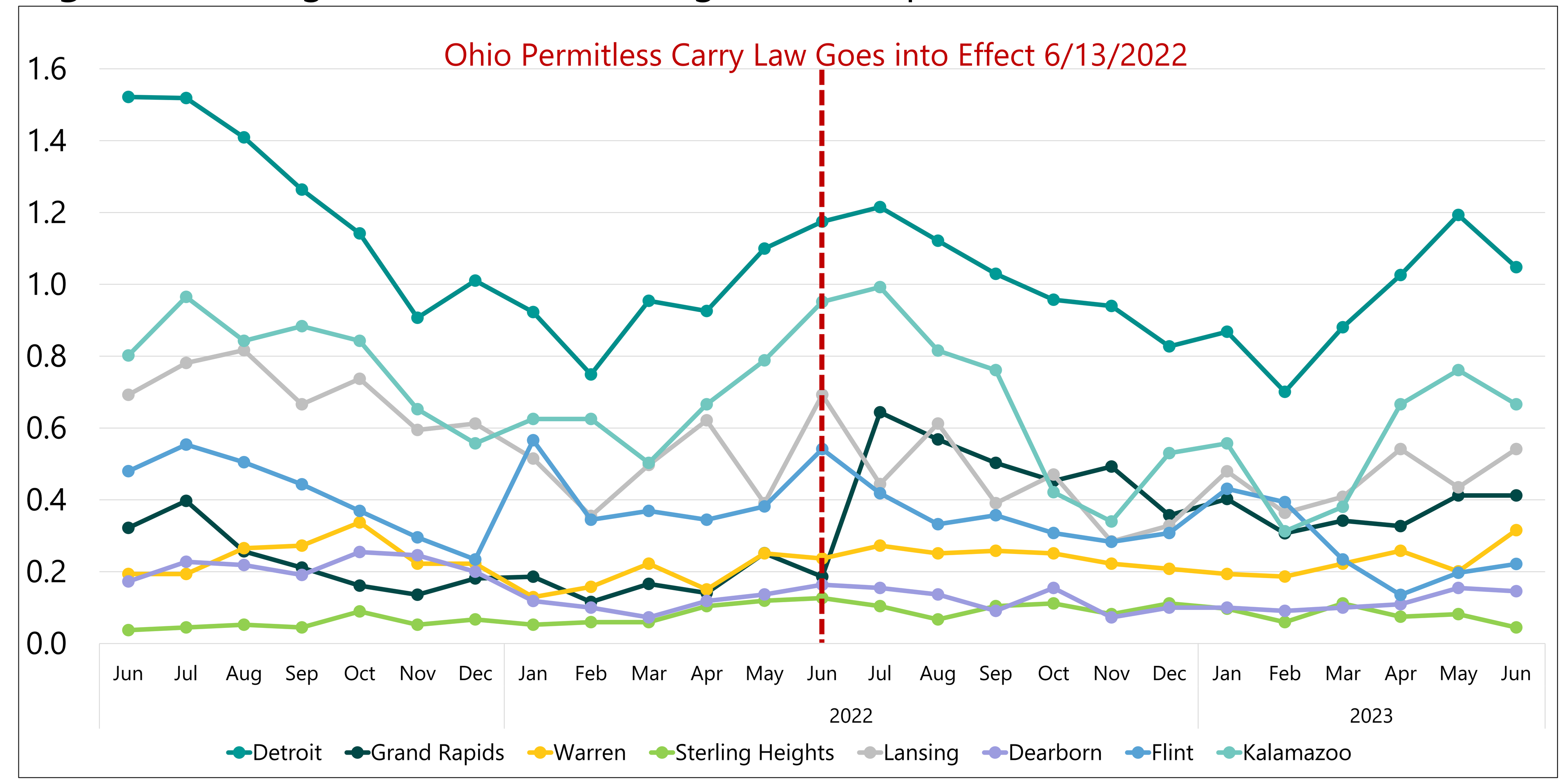


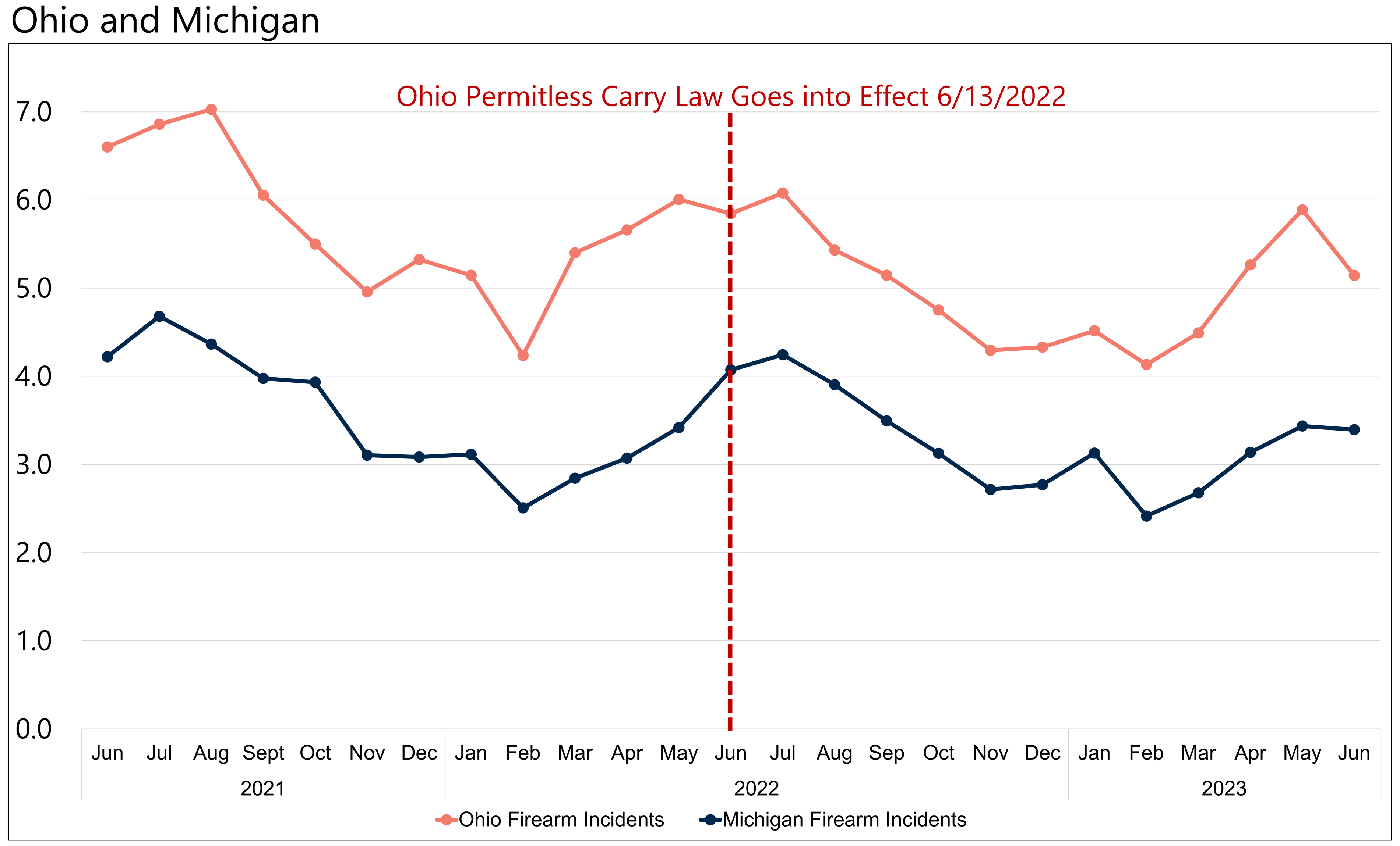
Table 1. MK and Independent Samples T-Test Results (OH). Significant findings are bolded.

	Mann-Kendall Trend Test			Independent Samples T-Test		
City	tau	*p*-value	Sen's Slope	*t*-value	*df*	*p*-value
Columbus	**-0.231**	**0.02**	**-2**	**2.007**	**48**	**0.05**
Cleveland	-0.19	0.056	-0.778	0.645	48	0.522
Cincinnati	-0.047	0.642	-0.279	-0.482	48	0.632
Toledo	**-0.263**	**0.018**	**-0.566**	**2.613**	**40.3**	**0.013**
Akron	**-0.289**	**0.004**	**-0.775**	**2.87**	**48**	**0.006**
Dayton	-0.041	0.692	-0.055	-0.801	48	0.427
Parma	-0.187	0.064	-0.125	**2.42**	**48**	**0.019**
Canton	-0.075	0.458	-0.078	0.709	48	0.481
All Cities Combined	**-0.209**	**0.035**	**-4.5**	1.396	48	0.169

Table 2. MK and Independent Samples T-Test Results (MI). Significant findings are bolded.

	Mann-Kendall Trend Test			Independent Samples T-Test		
City	tau	*p*-value	Sen's Slope	*t*-value	*df*	*p*-value
Detroit	**-0.28**	**0.004**	**-2.5**	1.564	48	0.124
Grand Rapids	**0.26**	**0.008**	**0.44**	**-7.380**	**48**	**<0.001**
Warren	0.03	0.802	0.01	-0.763	48	0.449
Sterling Heights	**0.26**	**0.011**	**0.08**	**-2.305**	**48**	**0.026**
Lansing	**-0.37**	**0.001**	**-0.35**	**3.190**	**48**	**0.003**
Dearborn	**-0.04**	**0.001**	**-0.11**	**2.220**	**48**	**0.031**
Flint	**-0.33**	**0.001**	**-0.19**	1.974	48	0.054
Kalamazoo	**-0.26**	**0.008**	**-0.25**	1.671	48	0.101
All Cities Combined	**-0.26**	**0.009**	**-3.10**	0.974	48	0.335

Figure 3. Total Rates of Incidents Involving Firearms Per 1,000 Persons, Select Cities in Ohio and Michigan



Findings & Discussion

Findings
- Crimes rates in Ohio and Michigan show similar trends, including seasonal increases during spring and summer, both pre- and post-PCL. Seasonal highs in both states decreased each year.
- MK Trend Test
  - Significant decrease in Akron, Columbus, and Toledo, and across all 8 Ohio cities combined.
  - Significant decrease in Detroit, Lansing, Dearborn, Flint, Kalamazoo, and all 8 Michigan cities combined.
  - Significant increase in Grand Rapids and Sterling Heights.
- Independent Samples T-Test
  - Significant variations in the average number of incidents in Columbus, Akron, Parma, and Toledo, OH; Grand Rapids, Sterling Heights, Lansing, and Dearborn, MI, pre- and post- PCL.

Future Directions
- Extend the study timeframe to capture long-term trends.
- Examine additional cities in PCL and non-PCL states.
- Control for other variables known to have an influence on firearm crimes.

Northeastern University
College of Social Sciences and Humanities

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Residential Instability & Crime in Toledo: A 10-Year Time Series Analysis

Julia Bell, M.S.; Melissa W. Burek, Ph.D.; Eric M. Cooke, Ph.D.; Jaryt Salvo, MSA., MEd.; Stephanie Decroix, M.S.

Academy of Criminal Justice Sciences 2025 Annual Meeting
Denver, CO
Wednesday, March 12, 2025

Study Objective

- Explore the association between residential instability and crime across 92 census tracts in Toledo, Ohio, from 2010 through 2019.
- Examine how different measures of residential instability influence neighborhood crime.

Social Disorganization Theory

Adverse neighborhood characteristics → Social ties/networks → Informal social control → Crime and disorder

- Social disorganization as a neighborhood feature.[1]
- Residential instability [2, 3]
  - Limits economic resources
  - Yields conditions opportunistic to crime
  - Draws crime into the community

Literature Review – Residential Vacancies

- Residential vacancies have been significantly linked to neighborhood-level violent and property offenses.[4, 5, 6, 7]
  - Larceny and burglary.[8, 9, 10]
  - Homicide, aggravated assault, and gun assault.[11, 12]
  - Drug offenses, including higher rates of adolescent substance use.[13, 14, 15]

Literature Review – Rentals & Geographic Mobility

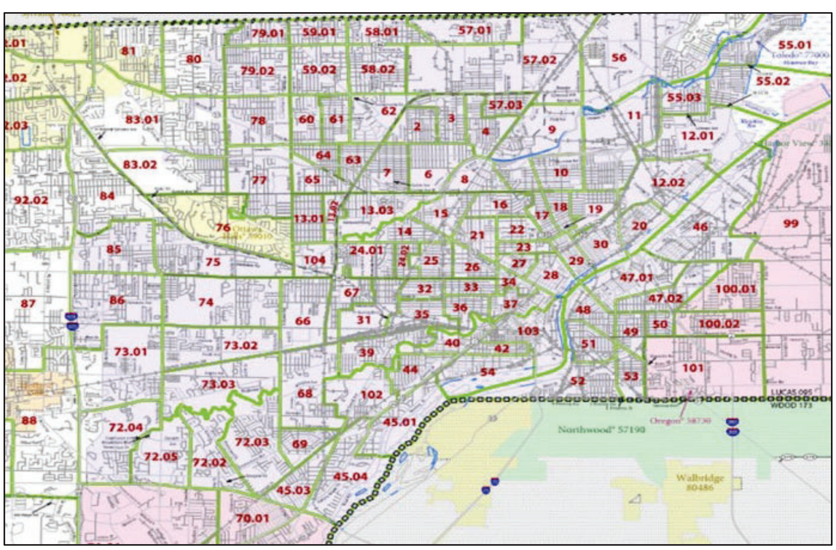
Renter-Occupied Housing Units

- Census blocks with higher rates of rental occupancy -> increased violent and property crime.[13]
  - Assault and robbery
- Housing tenure -> neighborhood-level burglary rates.[10]

Geographic Mobility

- Residential turnover -> risk of property victimization.[16]
- Increased younger/middle-aged persons moving into a neighborhood -> increased violent and property crime rates.[17]
  - Weakened social cohesion and control

2010 Toledo Census Tracts



Data

- 2010 - 2019
- 2010 Census Tracts
  - 92 included
  - 35 excluded
- United States Department of Housing and Urban Development (HUD) vacancy data
- 2010 Census and American Community Survey data
  - Demographics
  - Rentals/geographic mobility

Crime Incident Data

- Toledo Police Department's Intelligence and Special Investigations Bureau
- 2010 – 2019 Crime incident data
  - Crime type, address, date/time
- Data preparation
  - 145 crime types
    - Part 1 personal, Part 1 property, Part 2 personal, Part 2 property, public order, and substance offense
  - Tract identification through Census Geocoder
  - 548,154 included crime incidents

Measures

Vacancies

- Percentage of vacant addresses per tract

Rentals

- Percentage of the census tract population in renter-occupied housing units

Geographic mobility

- Percentage of persons per tract in the same house as they were 1 year ago

Crime Incident Type

- Part 1 personal, Part 1 property, Part 2 personal, Part 2 property, public order, and substance offense.
- Yearly counts

Analytical Plan

Multivariate Regression	Between-tract analysis
Vector Autoregressive Analysis (VAR) Cross-Lagged Panel	Within-tract analysis

Between-Tract Findings – Residential Vacancies

Table 1. Summary of Significant Multivariate Regression Findings for Percent Vacancies and Crime

Year	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Vacancy Percent Change	7.16%	7.8%	7.61%	7.96%	8.29%	8.65%	8.74%	9.35%	9.88%	10.27%
Crime Incident										
Part 1 Personal	3.8	-	5.3	4.18	6.77	4.49	5.16	-	2.53	2.92
Part 1 Property	-	-	-	-	27.17	-	-	-	14.61	17.16
Part 2 Personal	15.56	-	13.98	20.84	24.92	28.72	27.83	-	22.03	28.6
Part 2 Property	12.13	-	9.61	14.47	15.27	12.93	10.71	11.17	7.19	-
Public Order	-	-	-	31.66	39.8	31	31.85	-	-	-
Substance	-	-	12.05	22.47	34.03	25.79	25.71	23	26.89	28.74
Overall Crime	31.49	-	40.95	93.62	147.97	102.93	101.26	34.17	73.26	77.43

Between-Tract Findings – Rentals & Geographic Mobility

Rentals

- In 2010, an 21.5% incremental increase in renter-occupied housing units was associated with an additional 12.32 Part 2 property crime incidents.

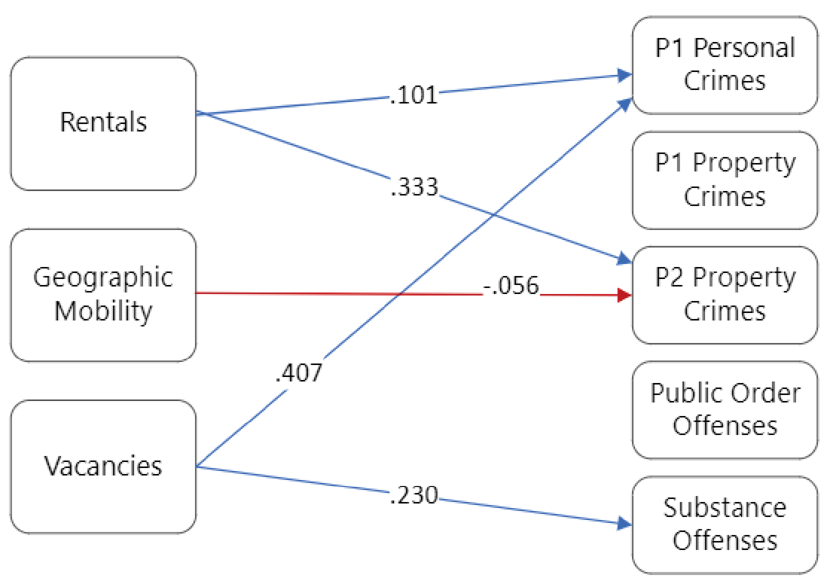
Geographic Mobility

- In 2014, an 8.32% incremental increase in geographic mobility was associated with approximately 15.04 less substance offenses.

Within-Tract Findings

- Rentals -> one Part 1 personal and 12 Part 2 property crimes.
- Geographic Mobility -> two Part 2 property crimes.
- Vacancies -> 4 Part 1 personal crimes 12 substance offenses

Figure 1. Significant Carryover Effects Within Tracts: Residential Instability Measures and Crime Incidents



Discussion

- Percentage of vacancies had the most substantial influence on crime incidents.
  - Between-tracts – significantly influenced crime incidents for all years except 2011.
  - Within-tracts – an incremental increase in vacancies was associated with 16 additional crime incidents.
- Both between- and within-tracts, the residential instability measures had a limited influence on public order incidents.
- Within-tracts, an increase in geographic mobility was associated with a decrease in Part 2 property offenses.
  - Consistent with social disorganization framework

References

1. Kubrin, C. E. (2009). Social disorganization theory: Then, now, and in the future. In *Handbook on crime and deviance* (pp. 225-236). New York, NY: Springer New York.
2. Nobles, M. R., Ward, J. T., & Tillyer, R. (2016). The impact of neighborhood context on spatiotemporal patterns of burglary. *Journal of Research in Crime and Delinquency*, *53*(5), 711-740.
3. Theodos, B., McTarnaghan, S., & Coulton, C. (2018). Family Residential Instability. *Urban Institute.*
4. Ellen, I. G., Lacoe, J., & Sharygin, C. A. (2013). Do foreclosures cause crime?. *Journal of Urban Economics*, *74*, 59-70.
5. Cui, L., & Walsh, R. (2015). Foreclosure, vacancy and crime. *Journal of Urban Economics*, *87*, 72-84.
6. Boessen, A., & Chamberlain, A. W. (2017). Neighborhood crime, the housing crisis, and geographic space: Disentangling the consequences of foreclosure and vacancy. *Journal of Urban Affairs*, *39*(8), 1122-1137.
7. Chen, X., & Rafail, P. (2020). Do housing vacancies induce more crime? A spatiotemporal regression analysis. *Crime & Delinquency*, *66*(11), 1579-1605.
8. Jones, R. W., & Pridemore, W. A. (2016). A longitudinal study of the impact of home vacancy on robbery and burglary rates during the US housing crisis, 2005-2009. *Crime & Delinquency*, *62*(9), 1159-1179.
9. Roth, J. J. (2019). Empty homes and acquisitive crime: Does vacancy type matter?. *American Journal of Criminal Justice*, *44*, 770-787.
10. Meng, Y. (2022). BURGLARY RATES AND NEIGHBORHOOD Contextual Characteristics: A Case Study in Hartford, Connecticut. *Northeastern Geographer*, *13*.
11. Suresh, G., & Vito, G. F. (2009). Homicide patterns and public housing: The case of Louisville, KY (1989-2007). *Homicide Studies*, *13*(4), 411-433.
12. Branas, C. C., Rubin, D., & Guo, W. (2012). Vacant properties and violence in neighborhoods. *International Scholarly Research Notices*, *2012*(1), 246142.
13. Raleigh, E., & Galster, G. (2015). Neighborhood disinvestment, abandonment, and crime dynamics. *Journal of Urban Affairs*, *37*(4), 367-396.
14. Furr-Holden, C. D. M., Lee, M. H., Milam, A. J., Johnson, R. M., Lee, K. S., & Ialongo, N. S. (2011). The growth of neighborhood disorder and marijuana use among urban adolescents: a case for policy and environmental interventions. *Journal of studies on alcohol and drugs*, *72*(3), 371-379.
15. Teixeira, S. (2015). "It Seems Like No One Cares" Participatory Photo Mapping to Understand Youth Perspectives on Property Vacancy. *Journal of Adolescent Research*, *30*(3), 390- 414.
16. Xie, M., & McDowall, D. (2008). The effects of residential turnover on household victimization. *Criminology*, *46*(3), 539-575.
17. Hipp, J. R., & Chamberlain, A. W. (2023). Who Leaves and Who Enters? Flow Measures of Neighborhood Change and Consequences for Neighborhood Crime. *Journal of Research in Crime and Delinquency*, *60*(5), 543-581.

Forecasting Crime Trends in Toledo, Ohio: A Prophet-Based Modeling Approach to Neighborhood-Level Analysis of Crime Trends

Jaryt Salvo, Julia Bell, Eric M. Cooke, Melissa W. Burek, & Emily Massie

Academy of Criminal Justice Sciences, 2025 Annual Meeting
Denver, CO
Wednesday, March 12, 2025

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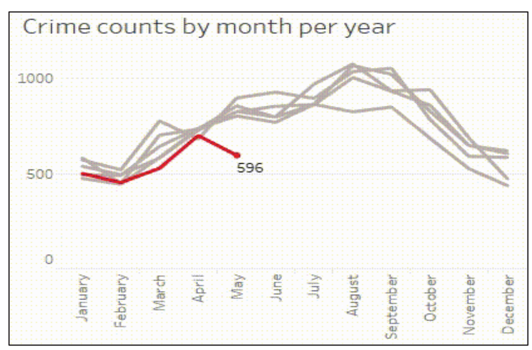
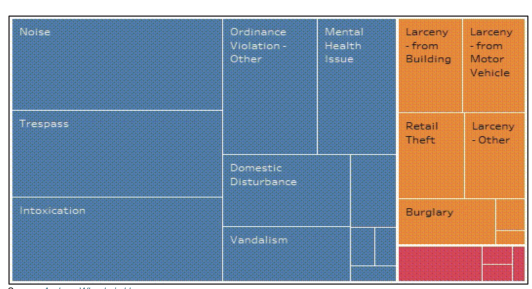
Background

- State of crime prediction research
  - Evolution of crime analysis
    - Growing emphasis on machine learning (ML) and AI-driven solutions
    - 59% of current approaches use supervised learning techniques
  - Spatial crime dynamics
    - 6-12% of urban areas identified as high-crime clusters
    - Temporal stability in neighborhood crime patterns





Source: Andrew Wheeler's blog

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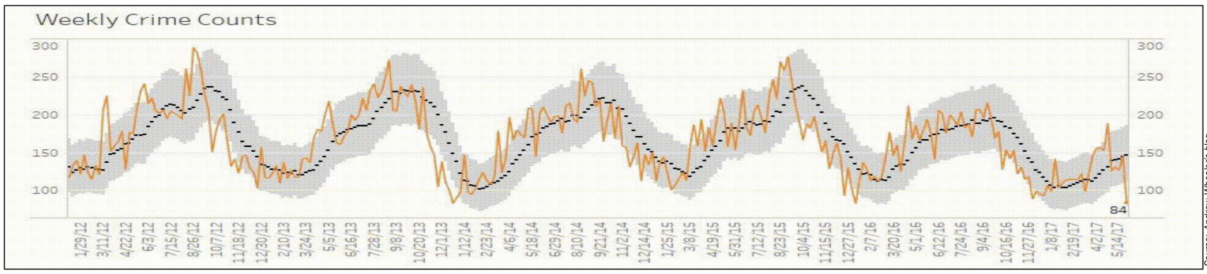
Background

- Gaps in current advanced forecasting
  - Limited integration of multiple temporal scales
  - Need for improved, lower-level, granularity
  - Lack of comprehensive seasonal pattern analysis
- Prophet model advantages
  - Reliable time-series predictive modeling
  - Accounts for seasonal variations and “holiday” effects
  - Robust to missing data and trend changes



Source: Andrew Wheeler's blog

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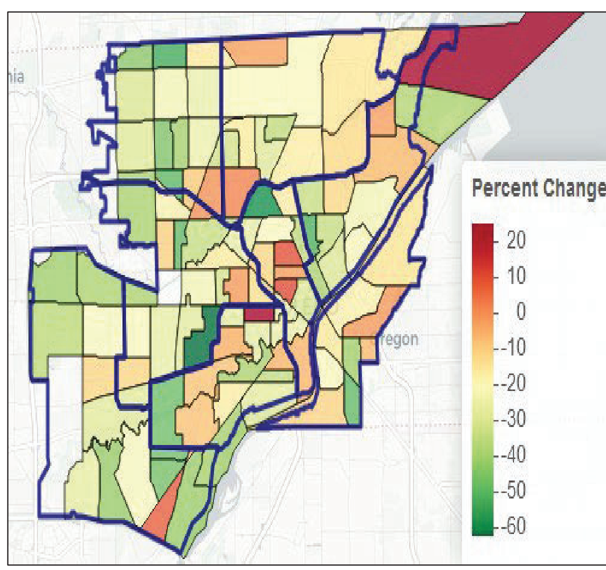
Purpose of the Study

- Develop data-driven tract-level crime forecasts
  - Part 1 and part 2 personal and property crimes
  - Public Order offenses
  - Substance-related offenses
- Examine predictive accuracy through Prophet modeling



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Method

- Data integration
  - Toledo Police Department (TPD) offense categories
  - Clean and prepare data for geocoding
  - Process geocodes for tract-level analysis
- Prophet model implementation
  - Additive regression model with trend components
  - Fourier series for seasonal patterns
  - Holiday effect integration

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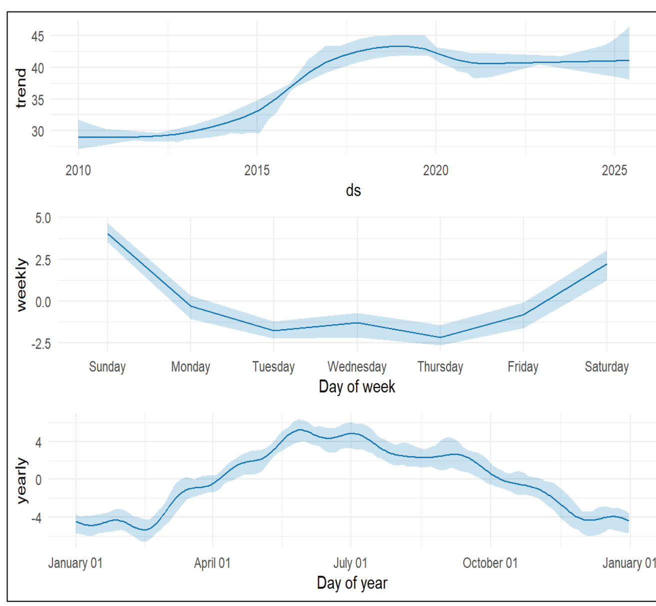
Analytic Framework

- Multi-scale analysis
  - Daily patterns
  - Monthly and yearly trends
- Model validation
  - Cross-validation across time periods
  - Comparative analysis with baseline model
  - RMSE, MAPE, & AIC comparison



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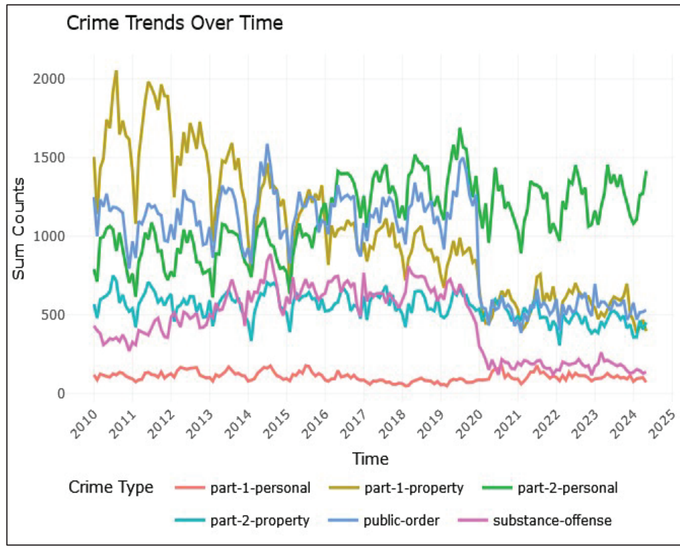
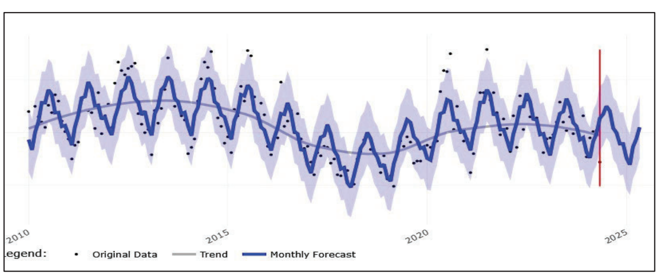
Layered Crime Trend Plots: Toledo, Ohio

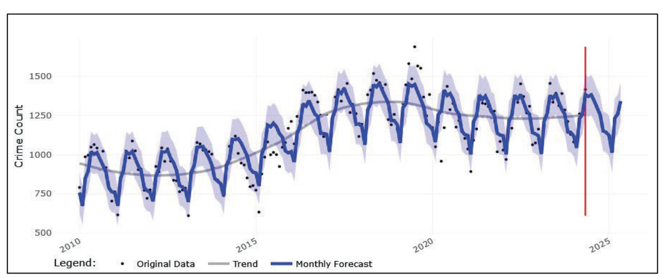
- Stacked visualization of offense categories from 2010-2025
- Monthly crime counts of each offense type
- Shows seasonal patterns and long-term trends across offense types



Part I and Part II Personal Crimes



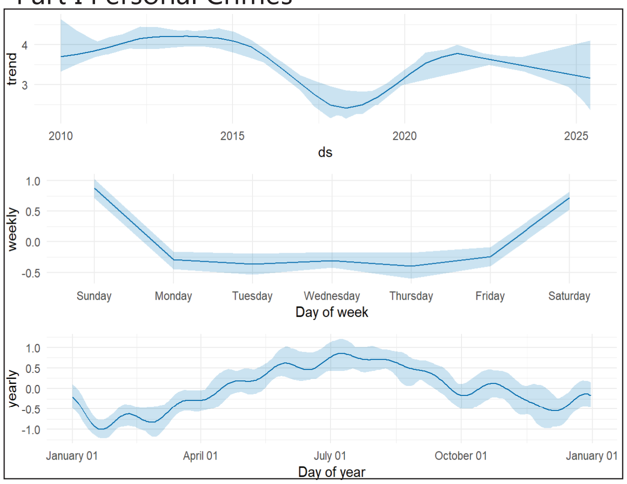
Part I Personal Crimes



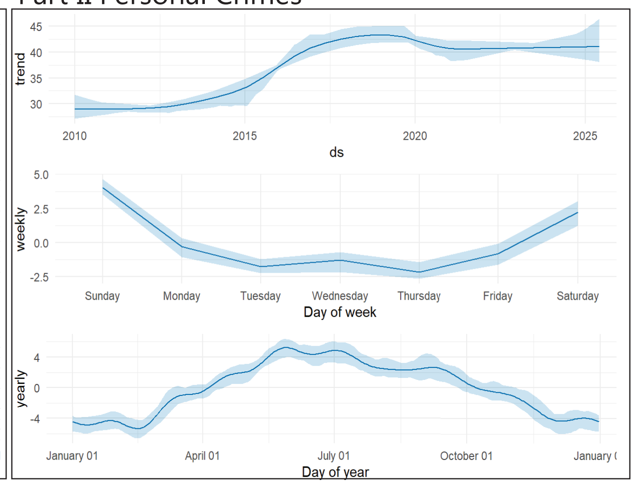
Part II Personal Crimes

Part I and Part II Personal Crimes - Decomposition

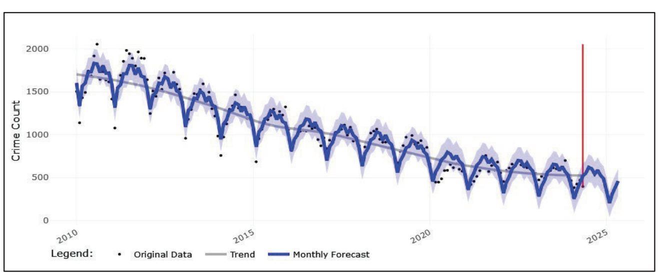
Part I Personal Crimes



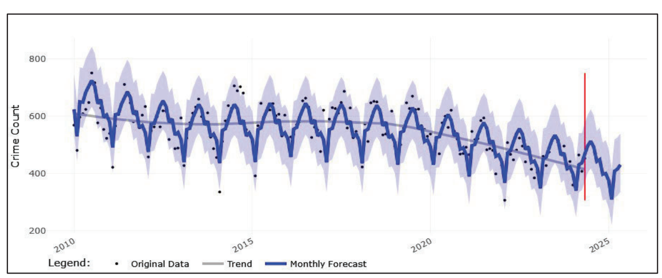
Part II Personal Crimes



Part I and Part II Property Crimes



Part I Property Crimes



Part II Property Crimes

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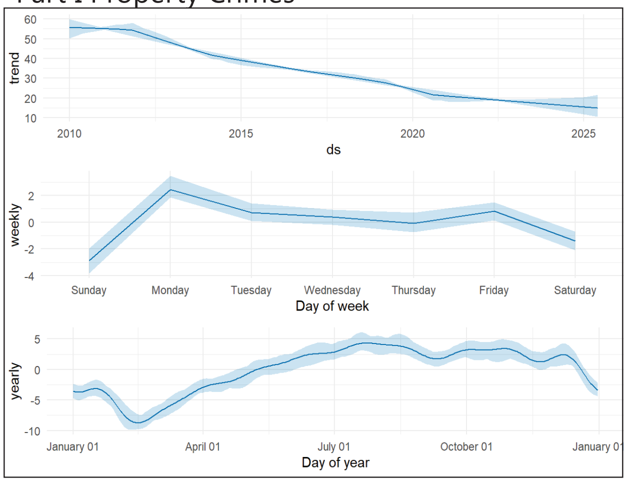
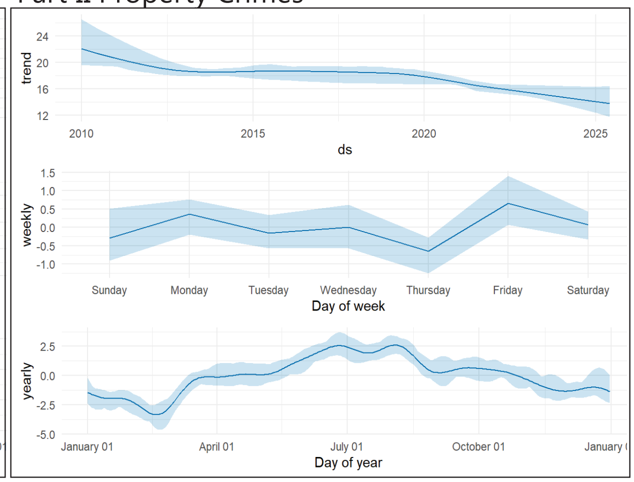
Part I and Part II Property Crimes - Decomposition

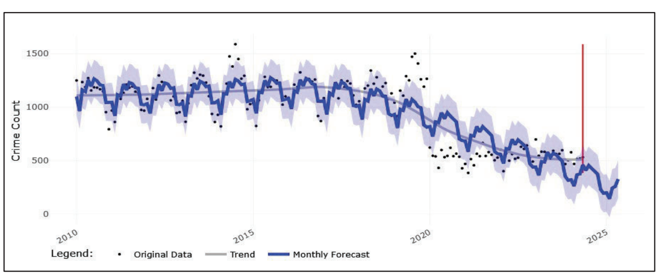
Part I Property Crimes



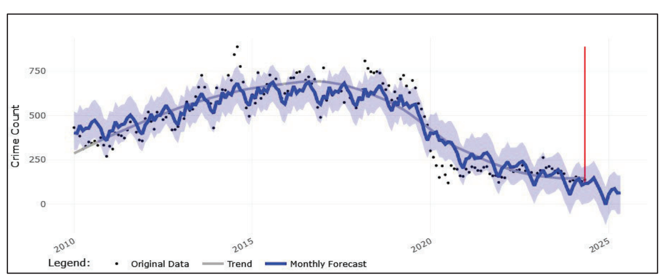
Part II Property Crimes



Public Order and Substance Offenses



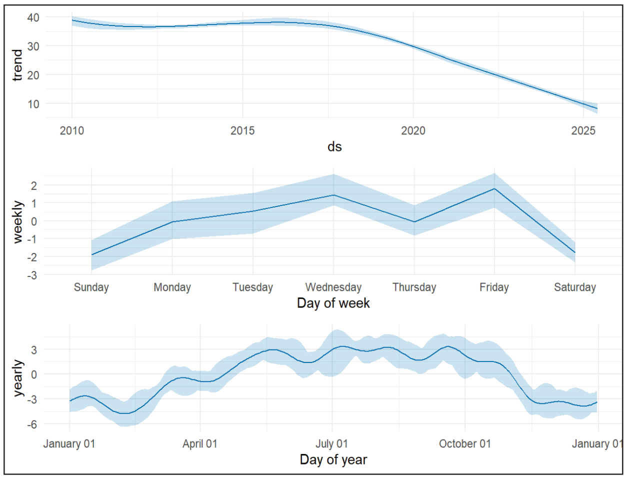
Public Order Offenses



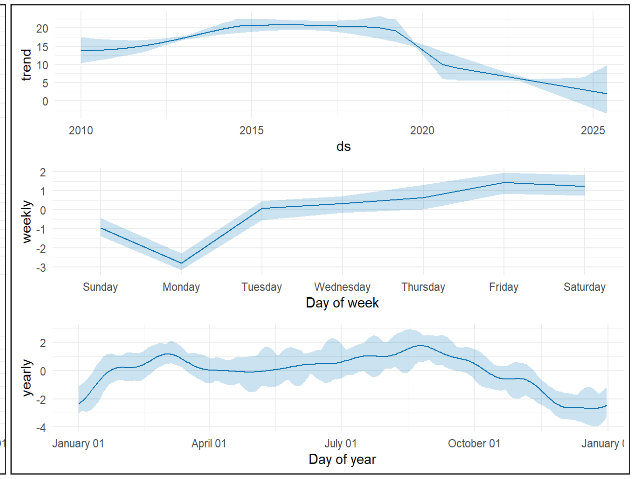
Substance-Related Offenses

Public Order and Substance Offenses- Decomposition

Public Order Offenses



Substance-Related Offenses



Summary

Personal crimes

- Inverse relation between Part 1 and Part 2
- High variability in both categories
- Possible zero-sum dynamics between types

Property crimes

- Both categories showing general decline
- Part 1 exhibits stronger downward trend
- Lower variability than personal crimes

Public order and substance-related offenses

- Significant 2020 distribution in both
- Pre-2020: Different trajectories
- Post-2020: Similar stabilization patterns

Future Directions

- **Model baselines**: Comparative analysis of Prophet forecasts against ARIMA benchmarks and other ML models (e.g., XGBoost, Random Forest, LSTM, & GRU)
- **Validation enhancements**: Implementation of rolling window and sliding window cross-validation
- **MLOps pipeline**: Development of end-to-end system for:
  - **Data ingestion**: Automated data storage and versioning
  - **Feature engineering**: Streamlined feature engineering and pre-processing
  - **Model training**: Reproducible model training workflows
  - **Model management**: MLflow integration for experiment tracking, model registry, and metadata logging
  - **Operationalization**: Deployment architecture for production forecasting with performance monitoring

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Forecasting Crime Trends in Toledo, Ohio: A Prophet-Based Modeling Approach to Neighborhood-Level Analysis of Crime Trends

Thank you!

Presented by: Jaryt Salvo
Email: jsalvo@bgsu.edu

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References

- Alsubayhin, A., et al. (2024). Review of crime prediction through machine learning. Journal of Criminal Justice.
- Feng, Y., et al. (2022). The comparative analysis of SARIMA, Facebook Prophet, and LSTM for road traffic injury prediction in Northeast China. Transportation Research.
- Jenga, K., et al. (2023). Machine learning in crime prediction. Journal of Criminal Justice.
- Kim, J., & Kim, S. (2024). A machine learning approach to analyzing crime concentration: The case of New York City. Journal of Quantitative Criminology.
- Mandalapu, R., et al. (2023). Crime prediction using machine learning and deep learning: A systematic review and future directions. IEEE Access.
- Nag, S., et al. (2022). An approach on cyber crime prediction using Prophet time series. IEEE Transactions.
- Safat, M., et al. (2021). Empirical analysis for crime prediction and forecasting using machine learning and deep learning techniques. IEEE Access.
- Wheeler, A. P., & Steenbeek, W. (2021). Mapping the risk terrain for crime using machine learning. Journal of Quantitative Criminology.

Appendix B

Project Documents

Forecasting Crime Trends in Ohio: A Brief on the Application of the Prophet Model to Toledo and Dayton Crime Incidents

Forecasting Crime Trends in Toledo, Ohio

Purpose

The purpose of the forecasting component of the Residential Instability project was to determine if crime patterns could be predicted using a computer model created by Meta called Prophet. By understanding crime patterns, cities can better allocate resources to improve public safety.

Method and Analysis

Crime incident data were obtained from the Toledo Police Department (TPD). The data were cleaned to correct for data entry errors or missing information. After cleaning, the crime incidents were aggregated by neighborhood level of analysis in units categorized in the US Census as tracts. While the lowest level of geographical analysis is this tract-level, the Prophet models utilized at this level struggled to capture meaningful predictive patterns because monthly counts at these levels were so low that predictions were not as meaningful. As such, in the "Results" section below, trends were reported at the city level.

The Prophet model was selected because it can handle different types of patterns over time, like daily spikes in crime, monthly shifts, or long-term trends. Prophet models constructed on the full city provide more robust trends and predictions.

One benefit of modeling crime counts with the Prophet model is its ability to capture trends at different time-scales — from daily to monthly trends, all the way to yearly trends. This trend layering is displayed in graphics called "Decomposition Plots," which compare patterns at the daily, monthly, and yearly levels. For each of our crime categories, we display both 1) its respective time series plot and 2) the model's decomposition plot.

In the time series plots, the actual crime count (i.e., original data we received from TPD) is represented as black dots. The Prophet model is drawn as a deep blue line with a surrounding light blue ribbon indicating the confidence interval. The red vertical line denotes the last month of TPD data that we collected. The deep blue line after this point shows predicted future crime counts resulting from the application of the Prophet model.

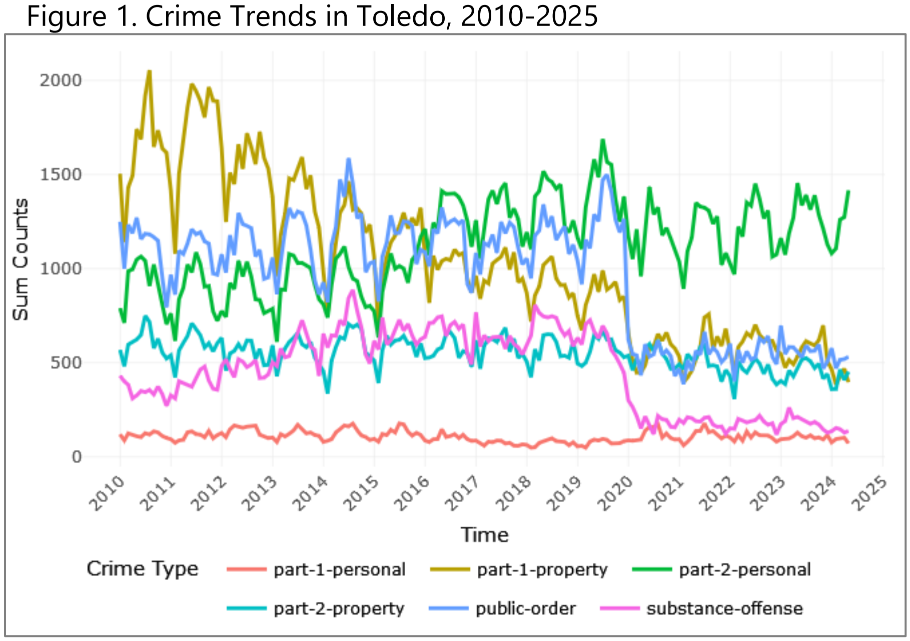
Results

The following are figures displaying crime patterns from 2010 to 2025. These included six main categories:

- Part 1 personal crimes,
- Part 2 personal crimes,
- Part 1 property crimes,
- Part 2 property crimes
- Public order offenses
- Substance-related crimes.

Resulting long-term trends as well as seasonal patterns (e.g., how some crimes increase in summer and decrease in winter) became apparent.

Figure 1. Crime Trends in Toledo, 2010-2025



Personal Crime Trends

We found that Part 1 and Part 2 personal crimes often moved in opposite directions. If serious personal crimes (Part 1) went up, less serious ones (Part 2) sometimes went down. There were clear weekly and yearly patterns—for example, more personal crimes occurred on weekends as well as in warmer months.

Figure 2. Toledo Part 1 Personal Crimes Time Series Plot

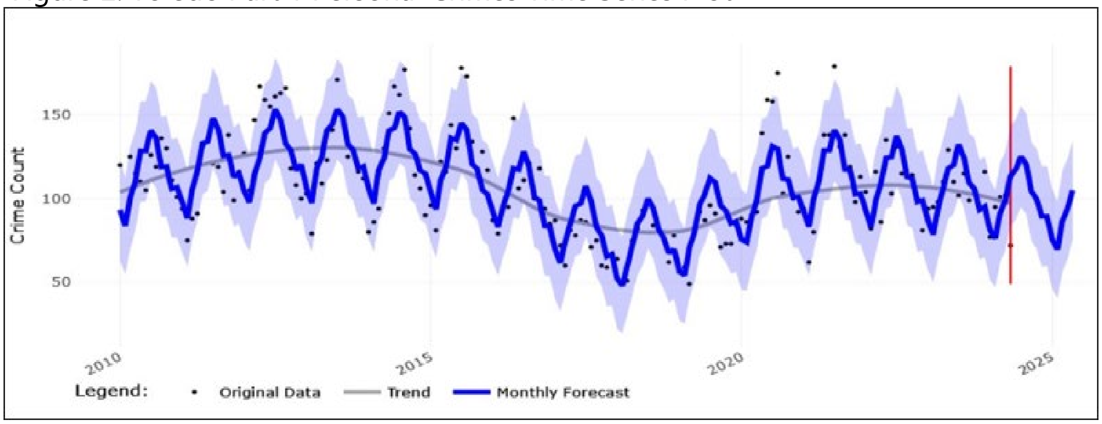


Figure 3. Toledo Part 1 Personal Crimes Decomposition Plots

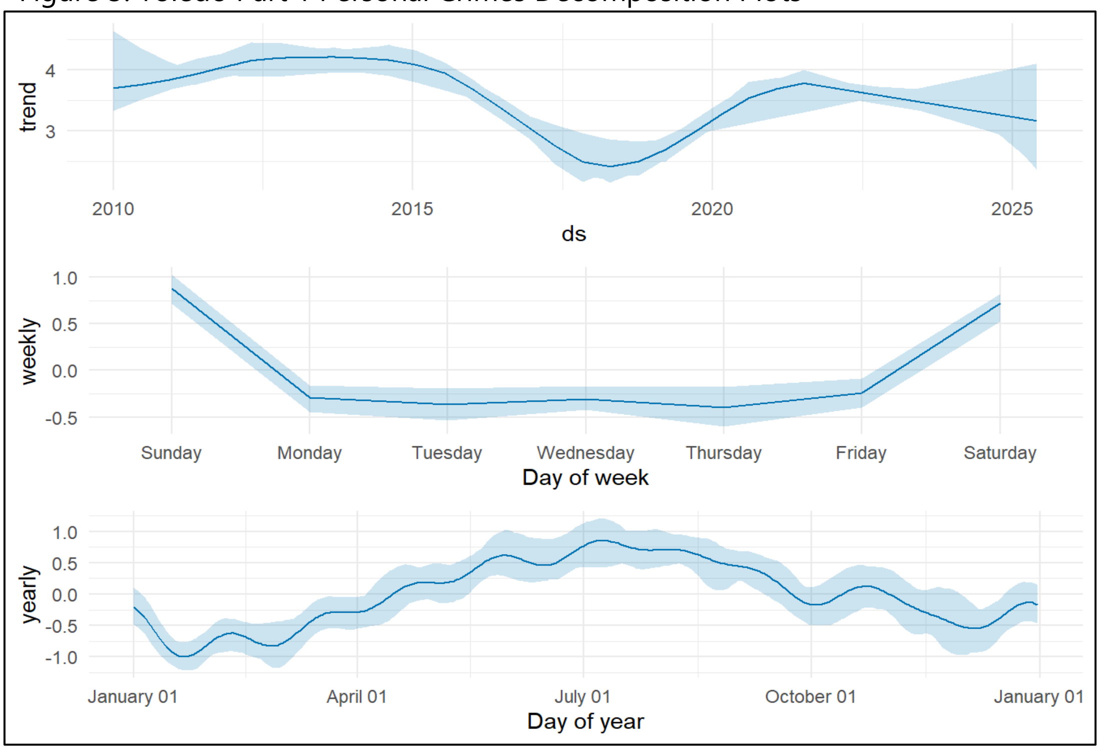


Figure 4. Toledo Part 2 Personal Crimes Time Series Plot

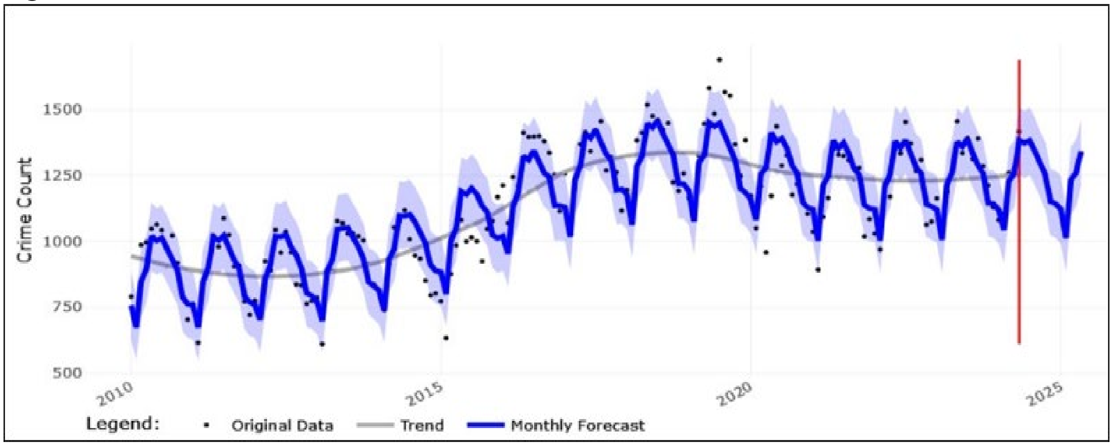
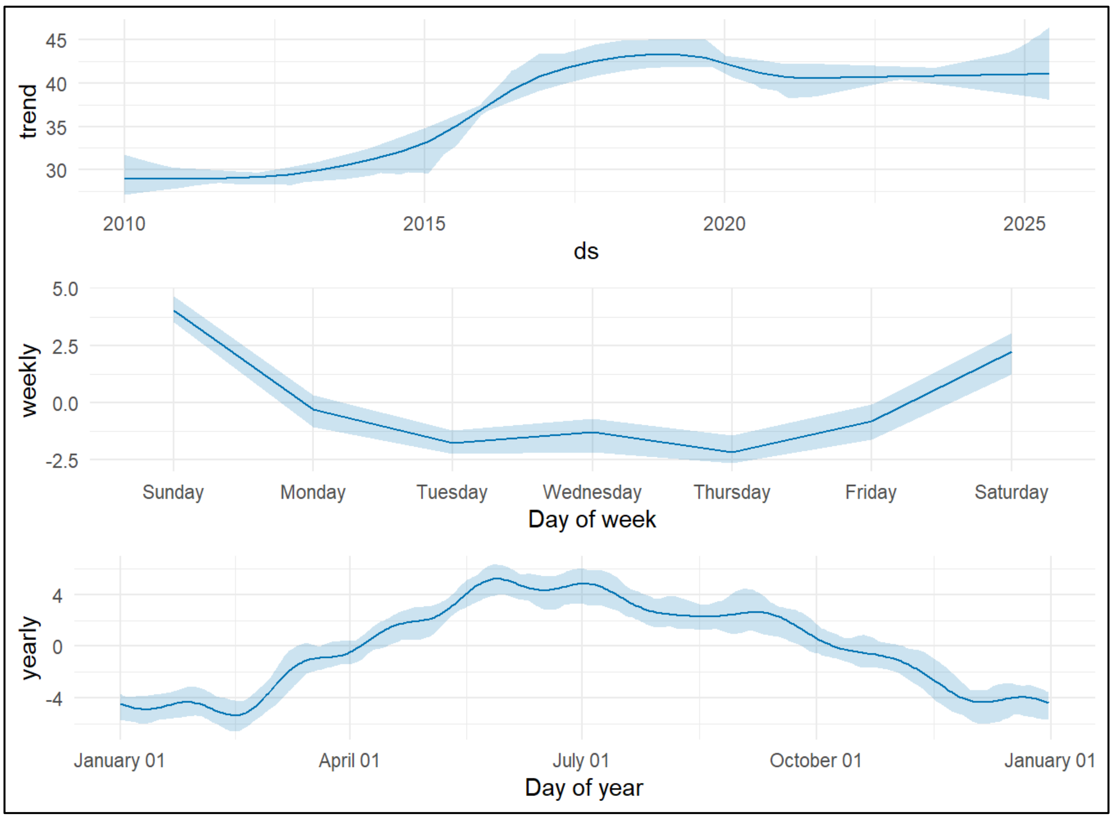


Figure 5. Toledo Part 2 Personal Crimes Decomposition Plots



Property Crime Trends

Part 1 property crimes, like burglaries, have been steadily decreasing each year. These crimes were less variable, making them more predictable than other crime categories. Part 2 property crimes were mostly stable, with a slight decrease starting in the last few years.

Figure 6. Toledo Part 1 Property Crimes Time Series Plot

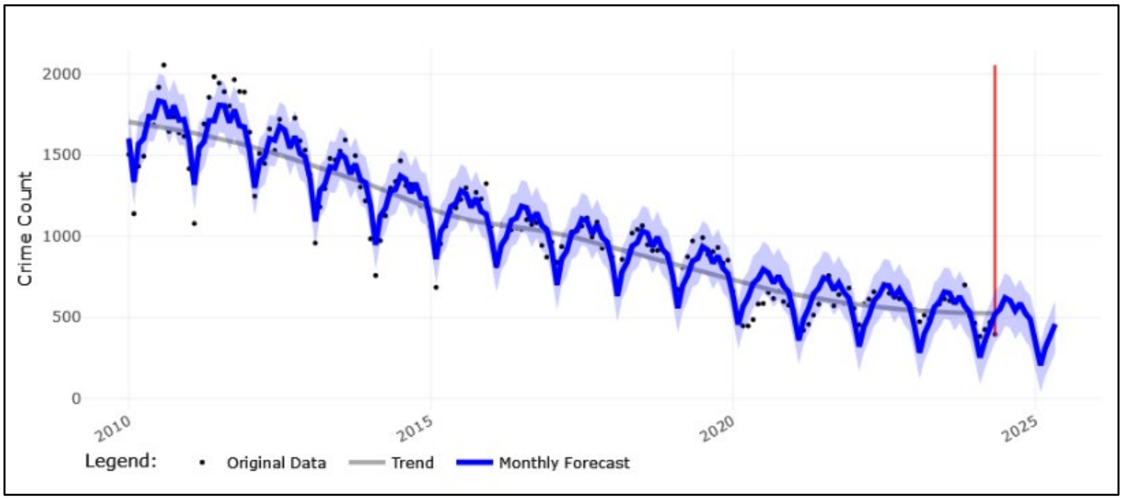


Figure 7. Toledo Part 1 Property Crimes Decomposition Plots

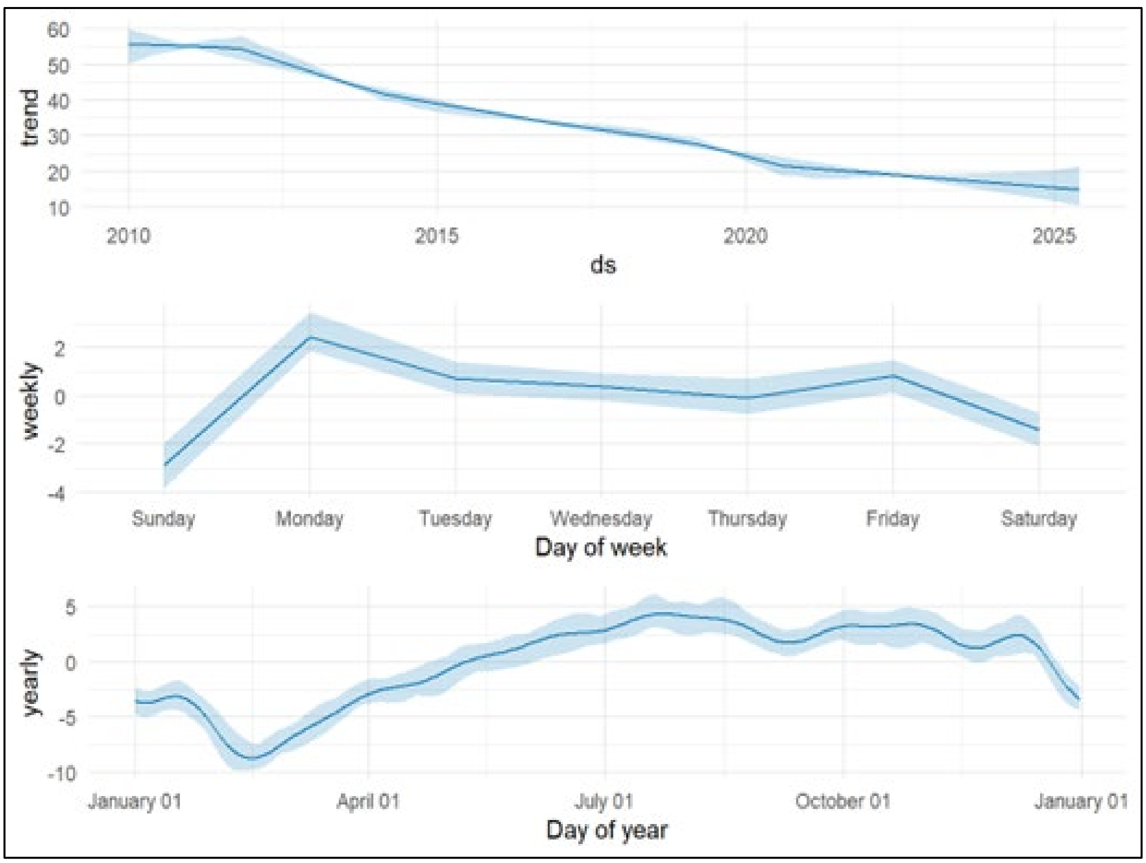


Figure 8. Toledo Part 2 Property Crimes Time Series Plot

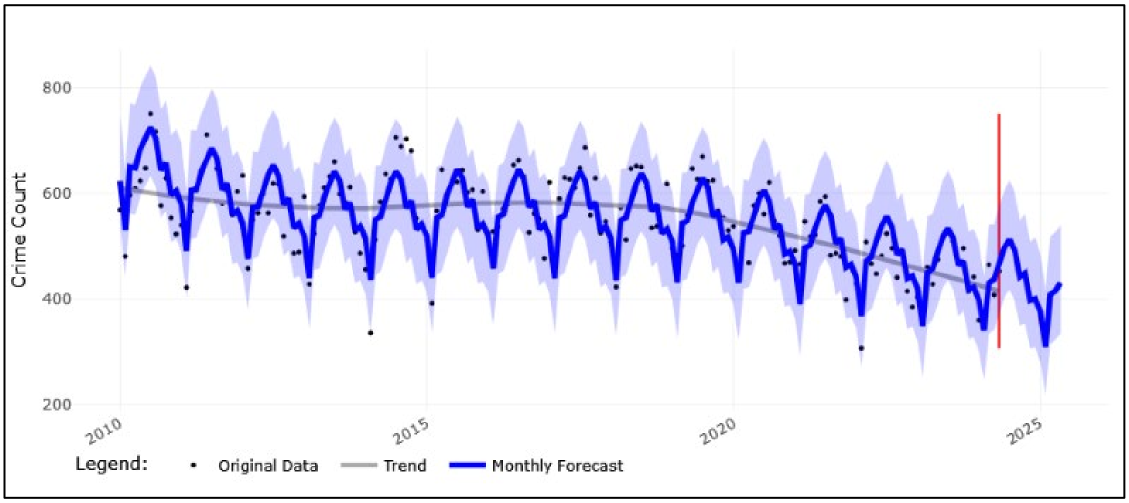
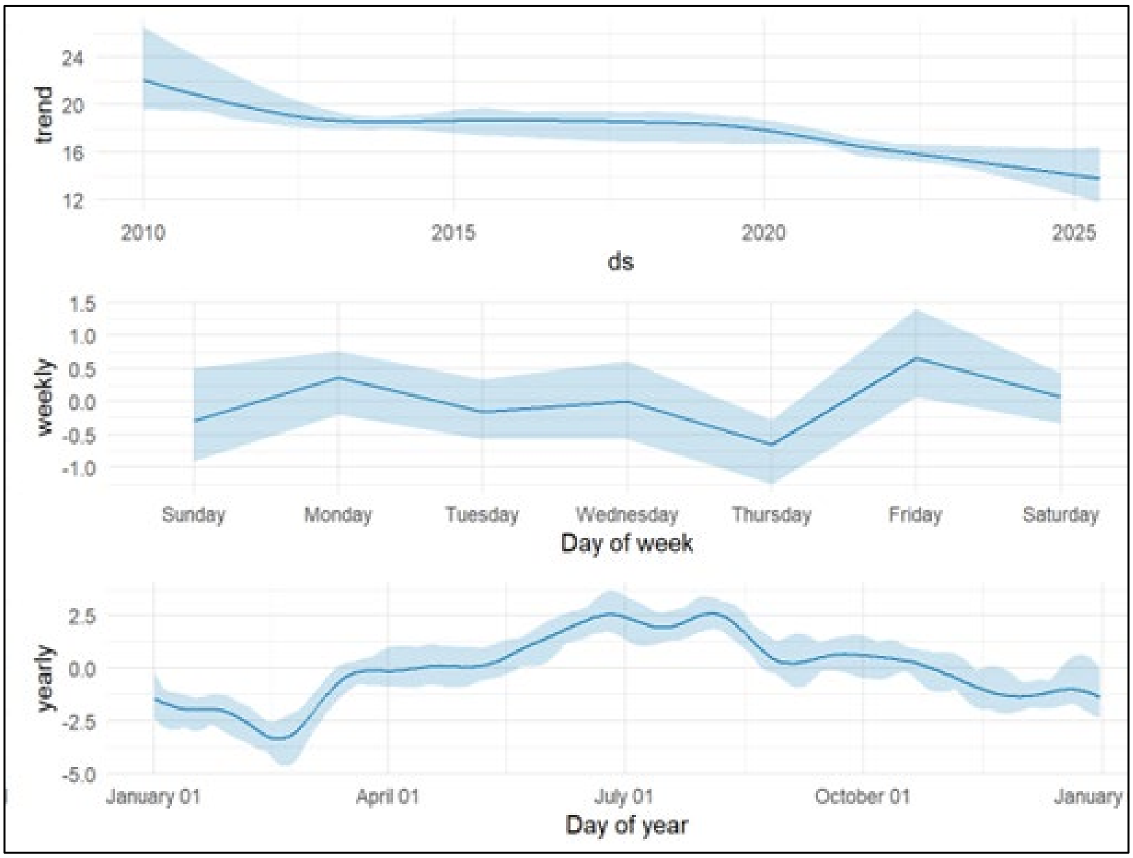


Figure 9. Toledo Part 2 Property Crimes Decomposition Plots



Public Order & Substance-Related Trends

Both types of crimes showed a significant drop in 2020. Before that year, public order crimes were relatively stable, and substance-related crimes were slowly rising. A clear "jump" downward in crime rates occurred in 2020 due to COVID-19. Prophet models struggle to predict sudden, non-linear changes like this because of its underlying mathematical equations mainly focus on linear trends and seasonal patterns. This limitation was especially noticeable in our public order crime forecasts, where Prophet's predictions did not fully match the rapid drop. Notice how the model tries to fit a holistic (connecting pre and post 2020) linear trend starting at 2020 versus a more intuitive brand-new trend that should be nearly flat at the "new normal" for each category post-2020.

Figure 10. Toledo Public Order Crimes Time Series Plot

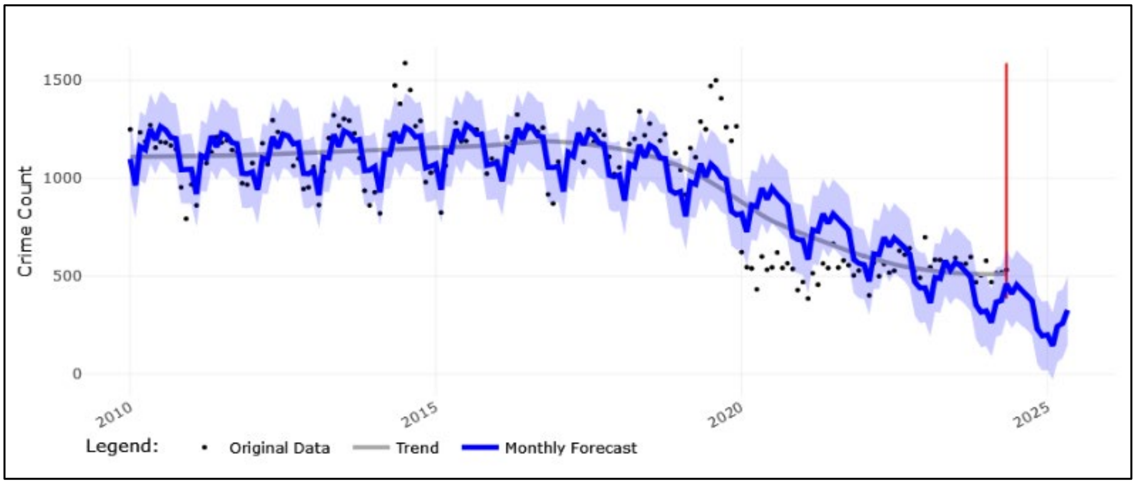


Figure 11. Toledo Public Order Crimes Decomposition Plots

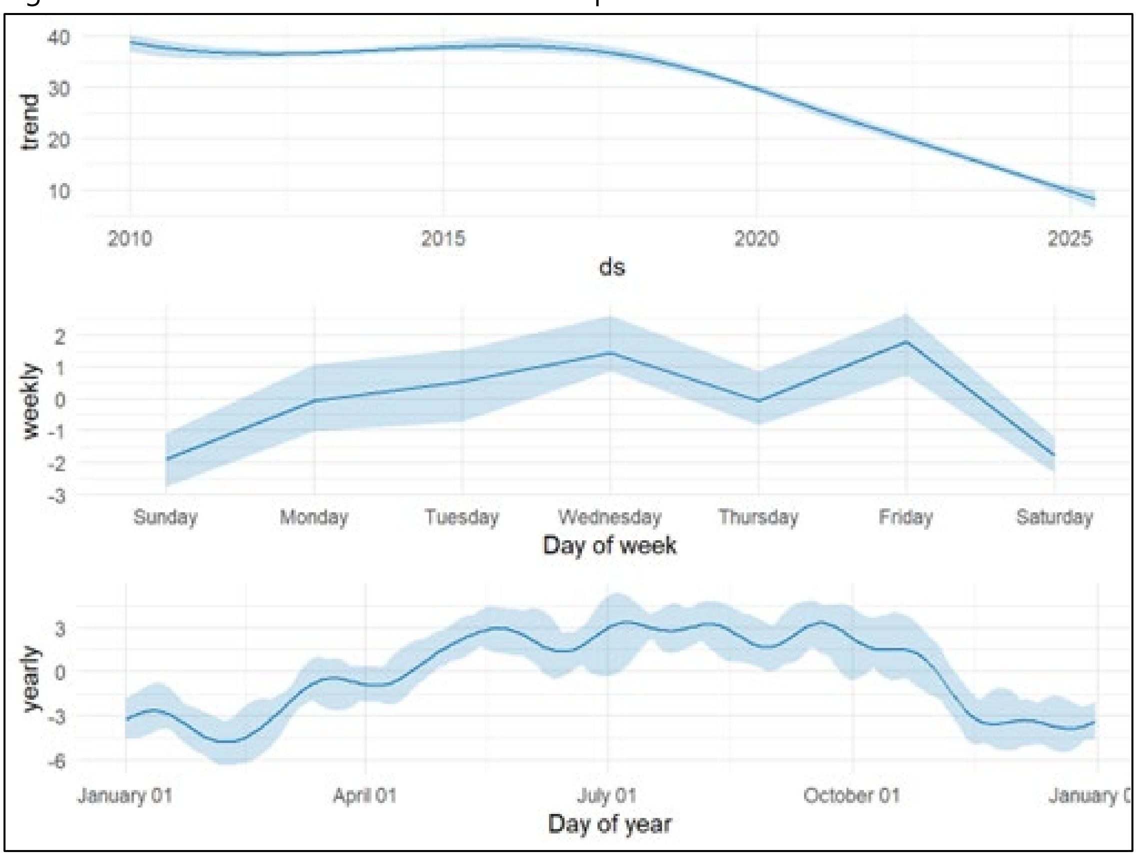


Figure 12. Toledo Substance-Related Crimes Time Series Plot

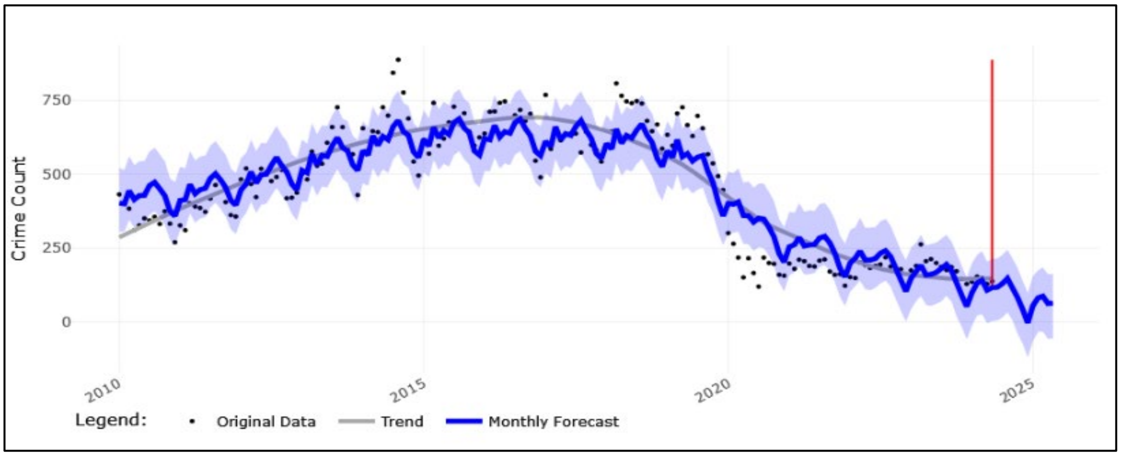
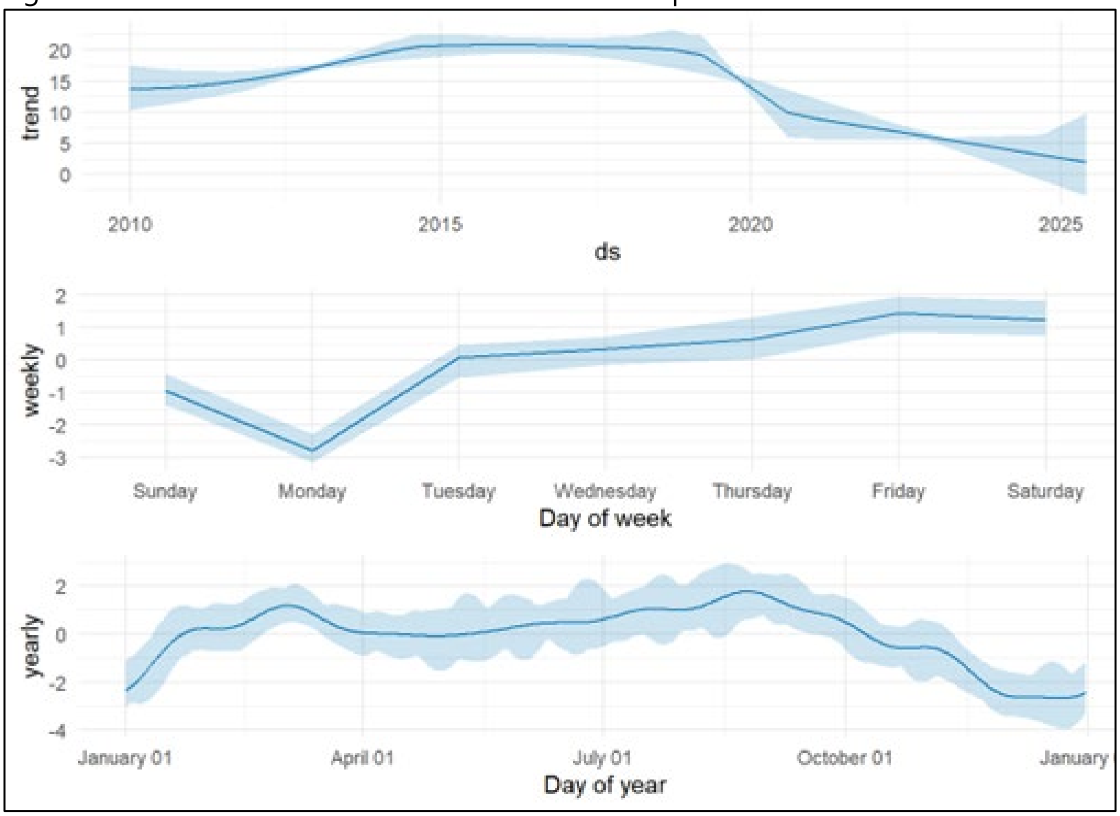


Figure 13. Toledo Substance-Related Crimes Decomposition Plots



Conclusion

Our analysis showed that personal crime categories often moved inversely, while property crimes generally declined steadily. Public order and substance-related crimes experienced sharp disruptions in 2020, highlighting Prophet's limitations in capturing sudden changes.

Future Research Directions

We want to compare Prophet to other models to see which predicts crime best. We also plan to test our model more carefully by checking its predictions at different levels of geographical scale. That is, while we prepared the data for tract-level modelling, many models did not fit well, going forward, we can group together tracts into bigger geographical regions such as police beats and sectors. Additionally, we will improve our analysis by adding models that can better handle unexpected, non-linear changes—like those seen during COVID-19.

Forecasting Crime Trends in Dayton, Ohio (Replication Study)

Building from the Toledo study, we applied the same crime prediction method in Dayton but adjusted it to look at police beats instead of tracts, as mentioned in the "Future Research Direction" in the Toledo brief, above. Dayton's data spanned from 2012 to 2020.

Background

We wanted to see if our crime prediction method worked just as well in another city. Prophet is good at dealing with multi-scaled time-series data and different time patterns, making it a useful choice for Dayton.

Purpose

We aimed to create reliable crime forecasts for Dayton's police beats. We wanted to see how accurately the Prophet model could predict crime trends and visualize the patterns at different levels of timescale.

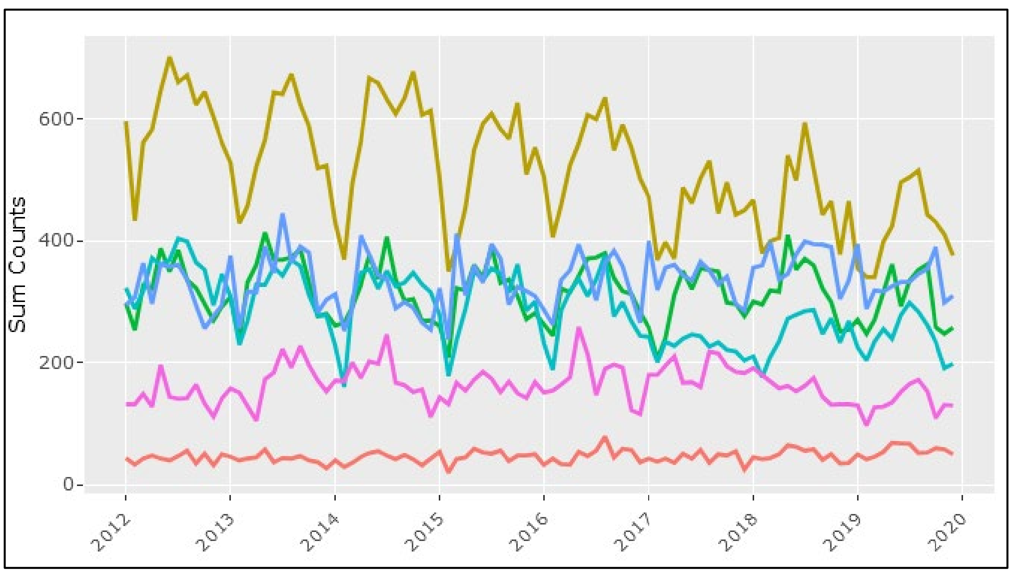
Method

We used similar steps as in Toledo: gathering data from the Dayton Police Department (DPD), cleaning it, and grouping it by police beats. A difference in terms of the data we received from TPD compared to DPD was that in Dayton, each crime was reported by year and month instead of year-month-day provided by TPD. This difference in data means that we do not have the ability to include daily trends of each crime category in the decomposition plots. This has a downstream effect of 1) having only two decompositions, by month and year; and 2) for the monthly decomposition, the trend is less smooth, that is, the ups and downs per month are more dramatic.

Results

The results of the Dayton Prophet study are presented below in a systematic manner, detailing crime trends at the police beat level from 2012 to 2020. First is our layered line plot for each crime category across all of Dayton from 2012-2020.

Figure 14. Crimes Trends in Dayton, 2012-2020



The visuals that follow display both the 1) time series plot and 2) the model's decomposition plot of the six different crime types in specific Dayton beats. This time, instead of grouping the full city's data per crime category, we focus on specific beats' trends and forecasts. This demonstrates Prophet's ability to perform more robustly than at the smaller tract level while also being more specific than at the city level. Each beat presented below was chosen as a close representation of the city-wide trend.

As a reminder: in terms of the time series plots, the actual crime count is represented as black dots, the Prophet model is drawn as a deep blue line, a confidence interval as a wider light blue ribbon, and a red vertical line indicates the last month in which we had data from the DPD. Looking beyond the red line, we see the Prophet model's predictions of future crime counts.

Personal Crime Trends

These are the plots for Dayton's West Patrol Operation Division (WPOD) Beat 2. We see a somewhat similar pattern as in Toledo; that is, there is a sense of trade-off between Part 1 and Part 2 personal crimes. In other words, as one increases, the other decreases and vice versa. Like Toledo, Part 1 personal crimes are highly variable from one month to another—some months very high, some very low—making it hard to predict.

Figure 15. Dayton Part 1 Personal Crimes Time Series Plot

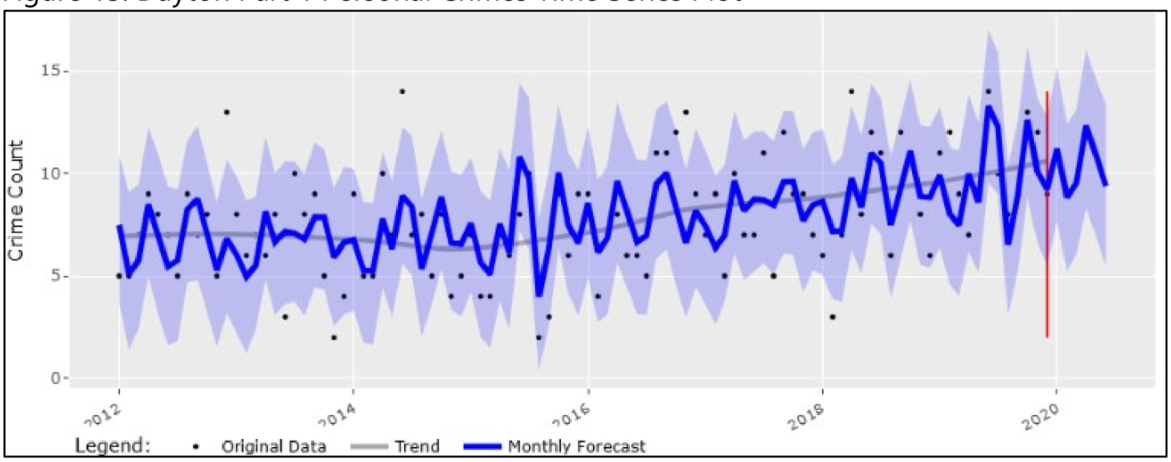


Figure 16. Dayton Part 1 Personal Crimes Decomposition Plots

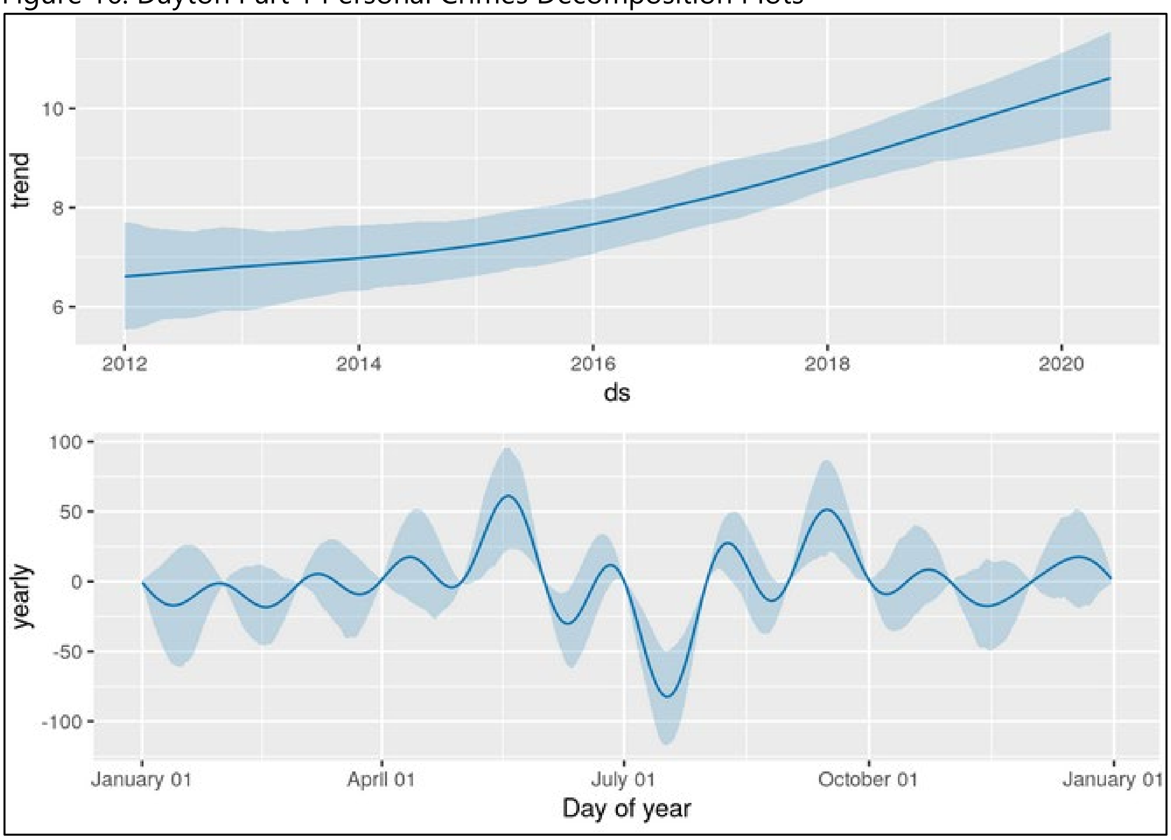


Figure 17. Dayton Part 2 Personal Crimes Time Series Plot

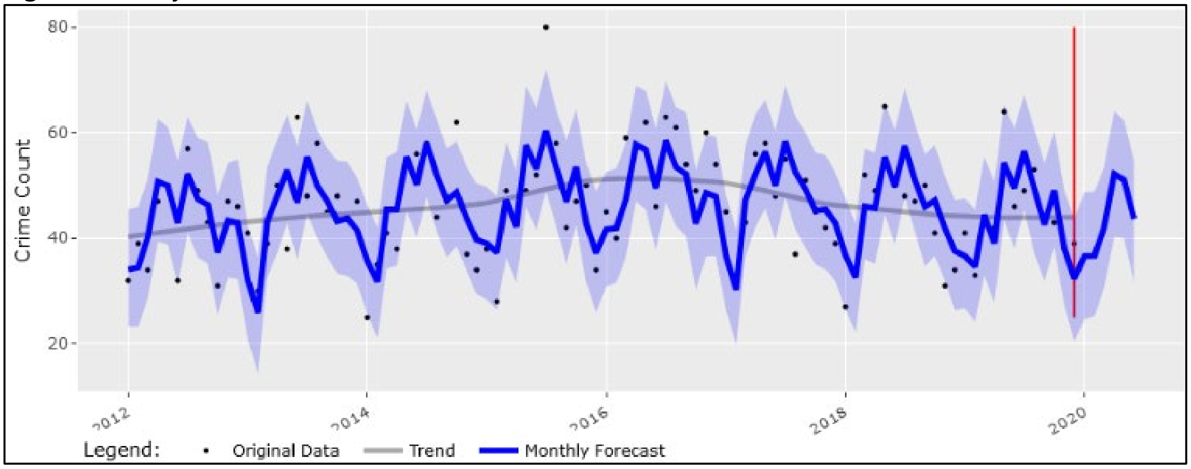
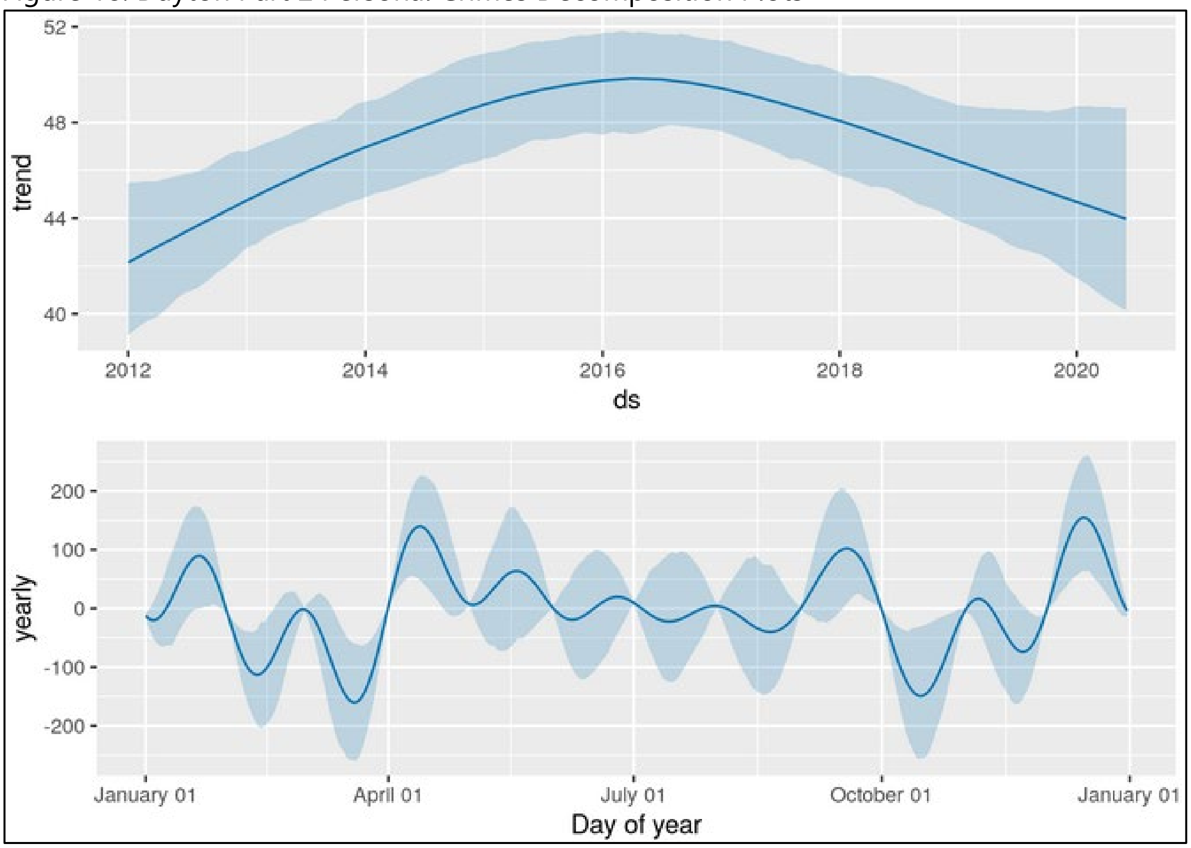


Figure 18. Dayton Part 2 Personal Crimes Decomposition Plots



Property Crime Trends

These plots are for the Central Patrol Operation Division (CPOD) Beats 1 and 2. Again, similar patterns to Toledo's, that is, a general downward trend where Part 1 property crimes drop faster than Part 2 property.

Figure 19. Dayton Part 1 Property Crimes Time Series Plot

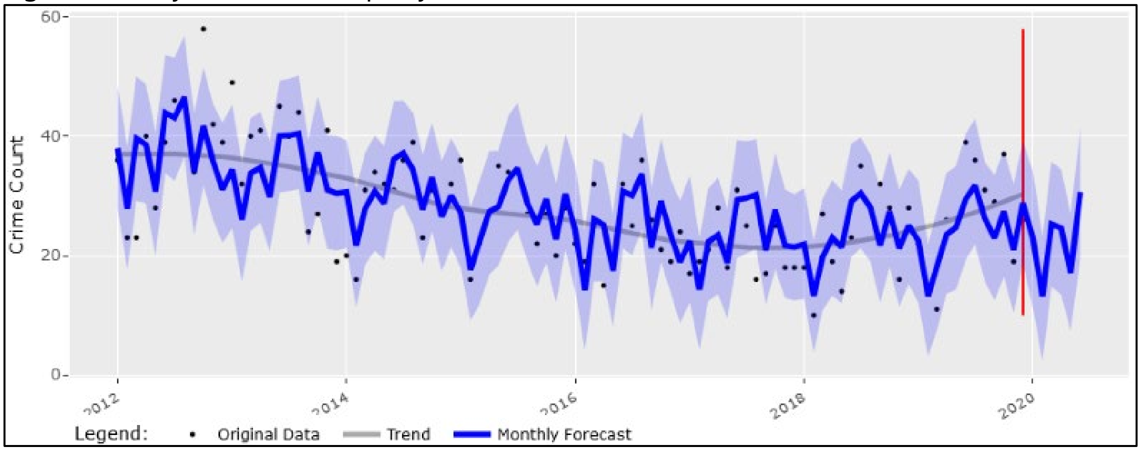


Figure 20. Dayton Part 1 Property Crimes Decomposition Plots

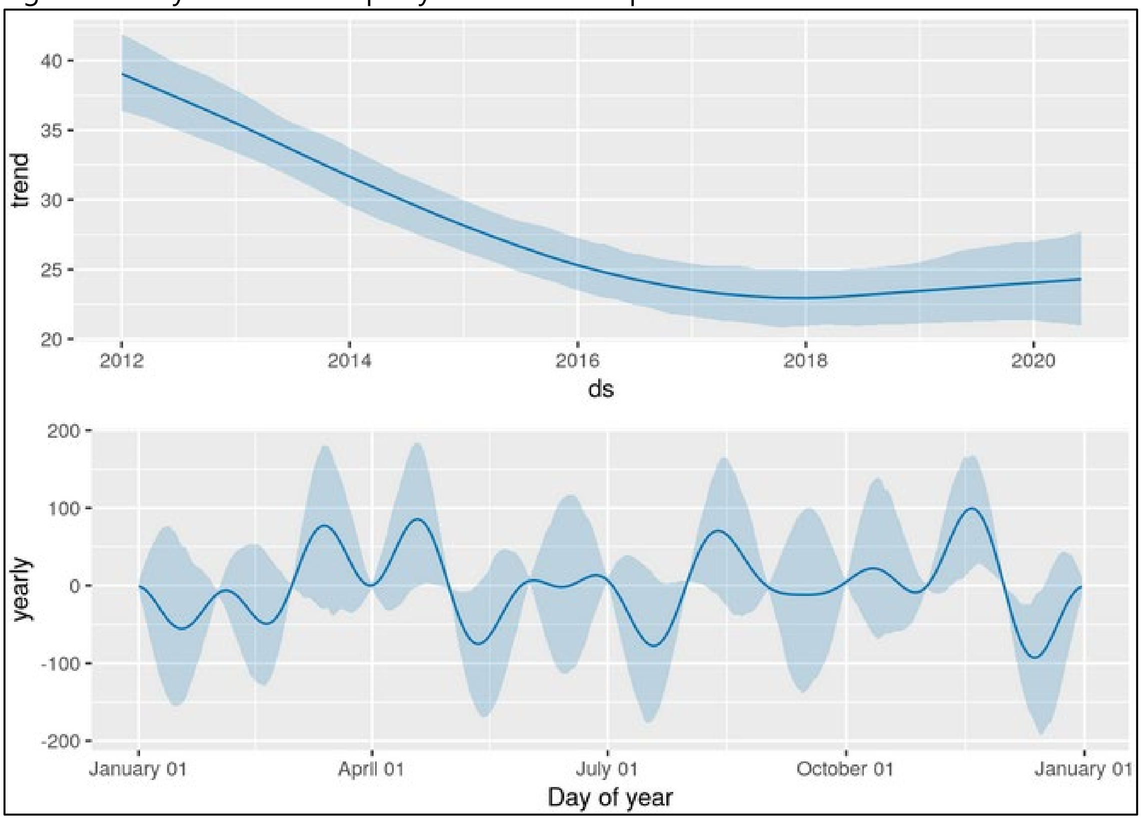


Figure 21. Dayton Part 2 Property Crimes Time Series Plot

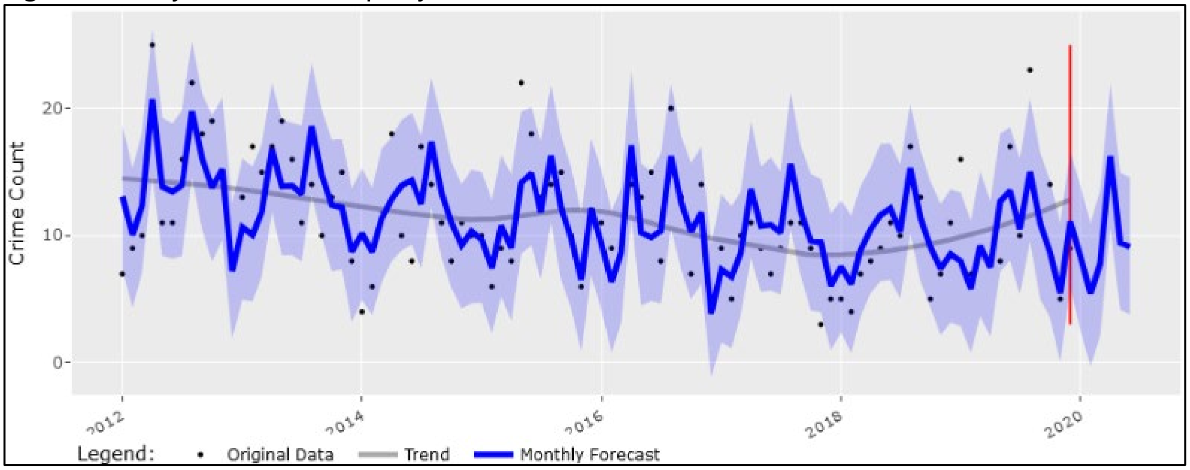
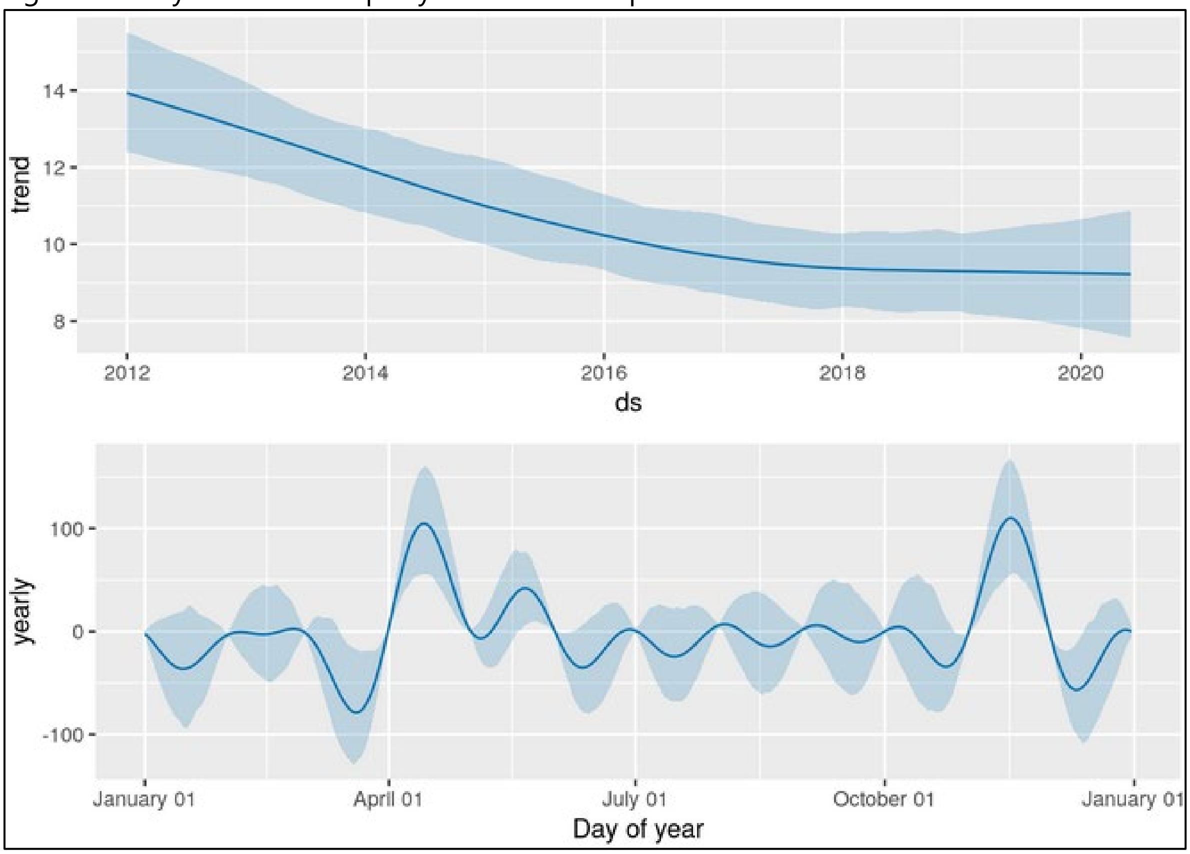


Figure 22. Dayton Part 2 Property Crimes Decomposition Plots



Public Order & Substance-Related Trends

These plots show trends in the East Patrol Operation Division (EPOD) Beat 4. Both types of crimes showed significant variability and deviation from the model, represented by a wide light-blue ribbon. Whereas public order offences were lowest in 2016, during that same year, substance-related offences were at their highest. Both types are bowl-shaped with public order being an upward facing bowl and substance-related offences being a downward facing bowl. At the end of the eight-year period, both counts end up being about the same as they started.

Figure 23. Dayton Public Order Crimes Time Series Plot

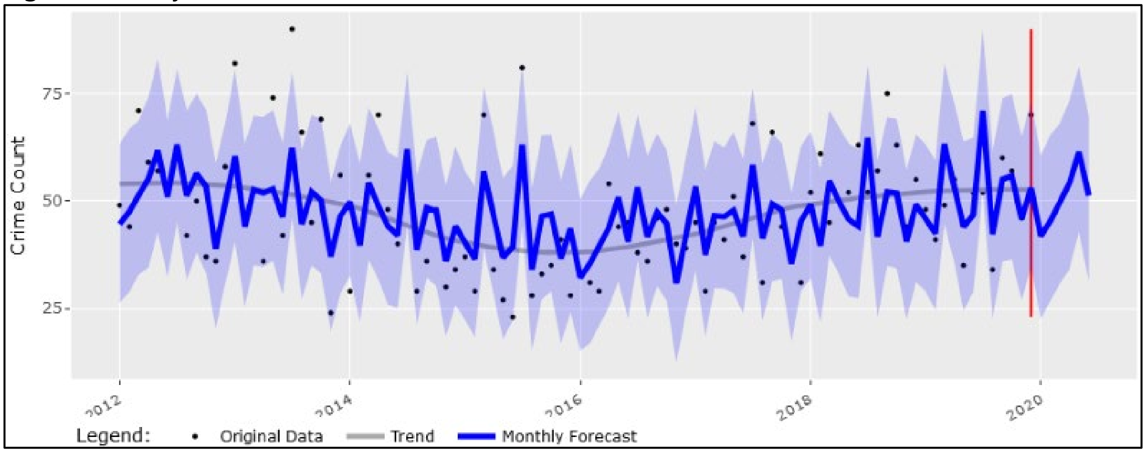


Figure 24. Dayton Public Order Crimes Decomposition Plots

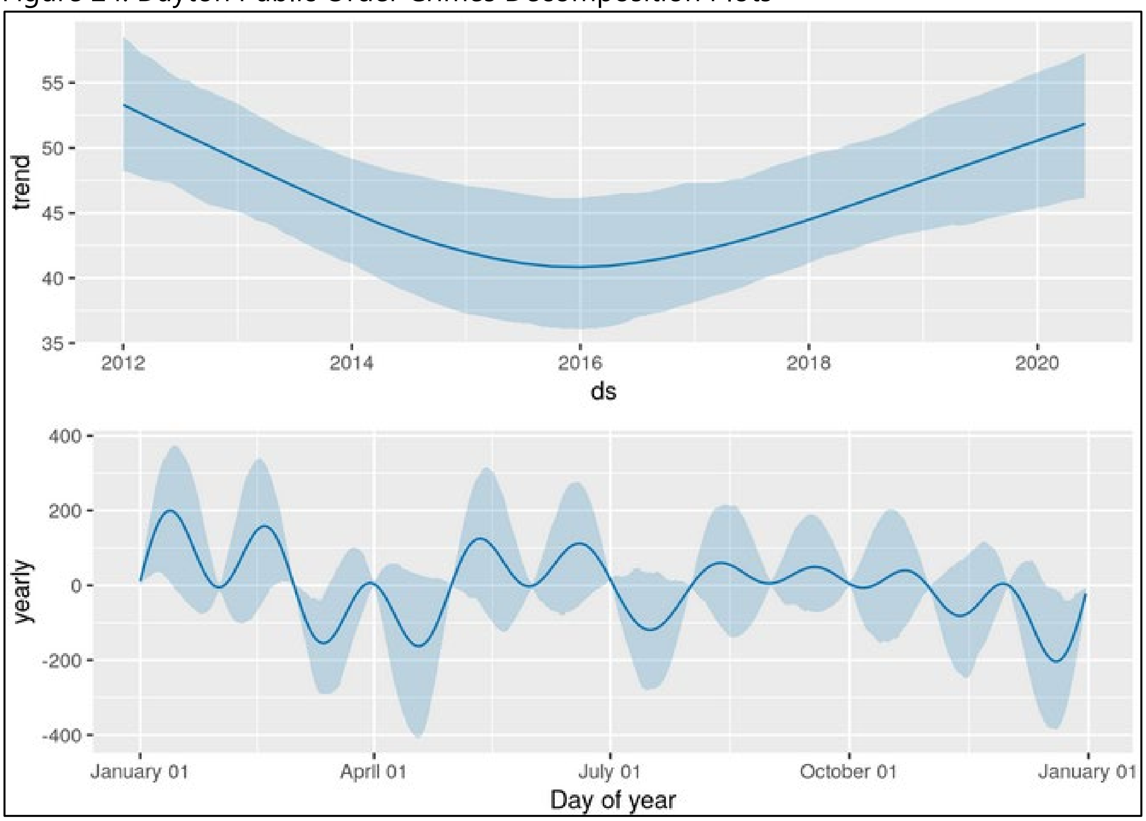


Figure 25. Dayton Substance-Related Crimes Time Series Plot

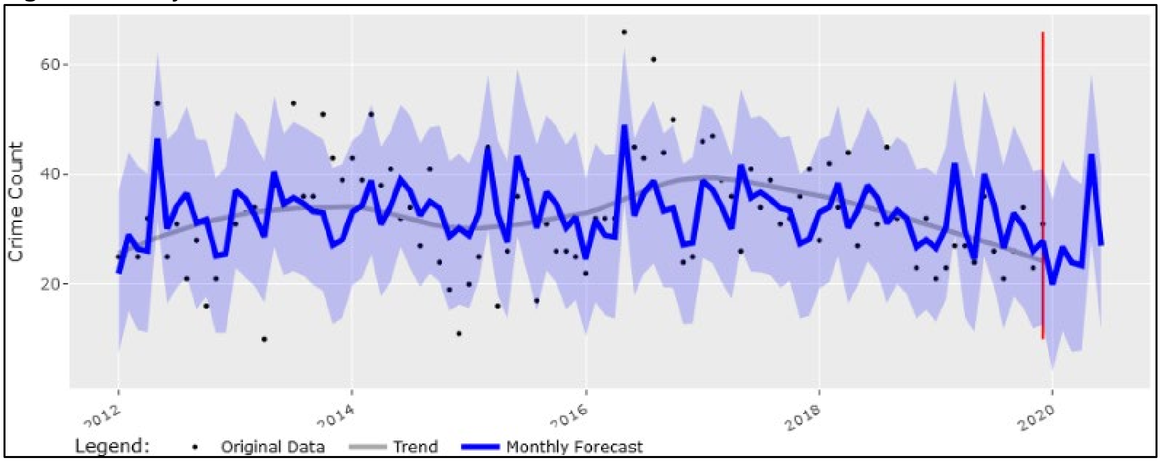
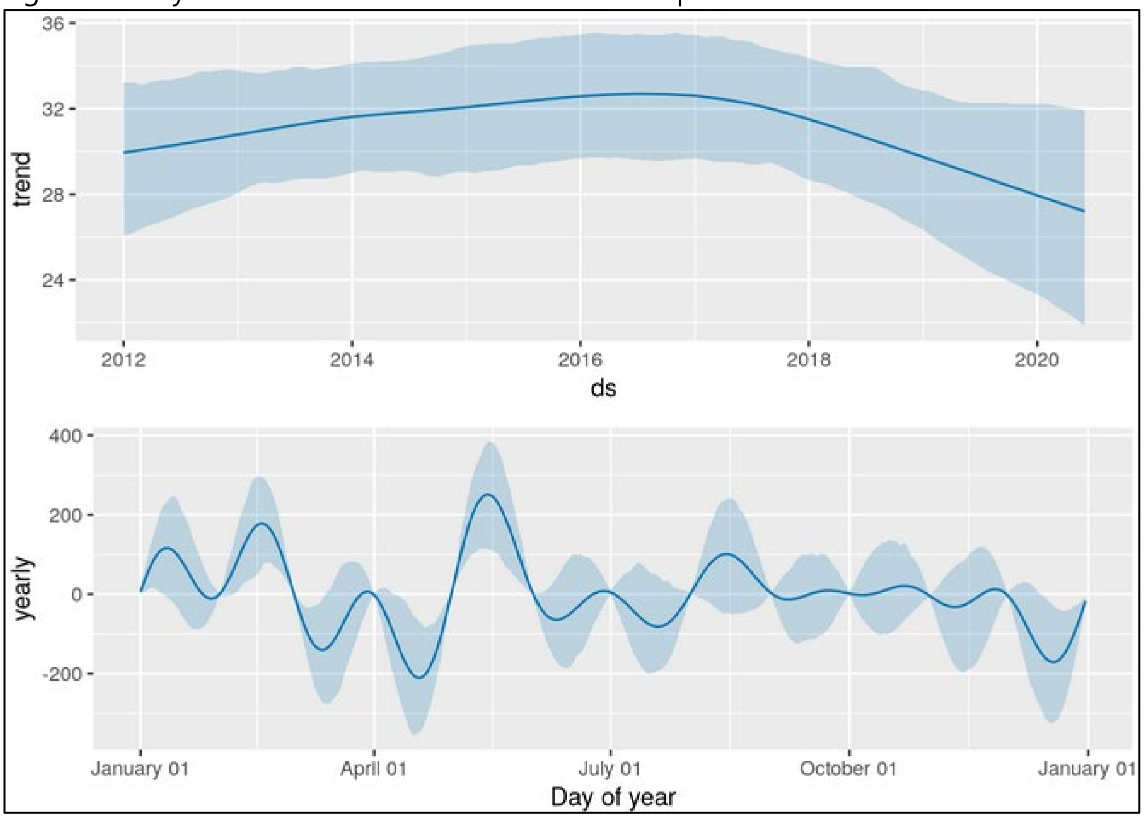


Figure 26. Dayton Substance-Related Crimes Decomposition Plots



Conclusion

Overall, the Dayton study showed similar crime trends to Toledo, including the inverse relationship between different crime categories and general downward trends in property crimes. Public order and substance-related crimes showed significant variability, with distinct patterns at different points over the years. The beat-level analysis helped demonstrate how Prophet could still be useful even when data detail is limited.

Future Research Directions

Moving forward, we plan to refine our forecasting approach. Specifically, we aim to better handle sudden changes like those seen in public order and substance-related crimes around 2020. Additionally, developing an automated crime forecasting system will make it easier to update and use these forecasts regularly, helping not only Dayton better manage and plan for crime prevention, but cities statewide. In the future, we hope to develop a crime reporting dashboard somewhat akin to the New York City Police Department's dashboard.

Permitless Carry and Crime Trends in Ohio and Michigan

Introduction

On June 13, 2022, Ohio enacted a permitless carry law (PCL), allowing Ohioans to obtain a firearm without a concealed-carry license. The Center for Justice Research (CJR) explored the relationship between permitless carry and crime incidents involving a firearm before and after the enactment of the PCL in the eight largest cities of Ohio and eight comparable cities in Michigan (which does not allow permitless carry) to observe general firearm crime trends in the two neighboring states.

After presenting this study at the Academy of Criminal Justice Sciences (ACJS) Annual Meeting in Denver, CO, the CJR received new data from the Michigan Incident Crime Reporting (MICR) allowing us to extend the timeframe by 12 months before and after PCL went into effect in Ohio. The updated datasets span June 2021-June 2024 in all selected cities*.

Table 1. Ohio Data

City	Source	Obtained Data
Akron	OIBRS	June 2020 – June 2024 crime incident data
Canton	OIBRS	June 2020 – June 2024 crime incident data
Cincinnati	OIBRS	June 2020 – June 2024 crime incident data
Cleveland	OIBRS	June 2020 – June 2024 crime incident data
Columbus*	OIBRS	June 2020 – December 2023 crime incident data
Dayton	OIBRS	June 2020 – June 2024 crime incident data
Parma	OIBRS	June 2020 – June 2024 crime incident data
Toledo	OIBRS	June 2020 – June 2024 crime incident data

*Columbus crime incident data is not yet available for 2024.

Table 2. Michigan Data

City	Source	Obtained Data
Dearborn	MICR	June 2020 – June 2024 crime incident data
Detroit	MICR	June 2020 – June 2024 crime incident data
Flint	MICR	June 2020 – June 2024 crime incident data
Grand Rapids	MICR	June 2020 – June 2024 crime incident data
Kalamazoo	MICR	June 2020 – June 2024 crime incident data
Lansing	MICR	June 2020 – June 2024 crime incident data
Sterling Heights	MICR	June 2020 – June 2024 crime incident data
Warren	MICR	June 2020 – June 2024 crime incident data

The following pages include illustrative figures and tables, as well as the results of statistical analyses performed.

Figure 1. Ohio Incidents Involving a Firearm per 1,000 Persons.

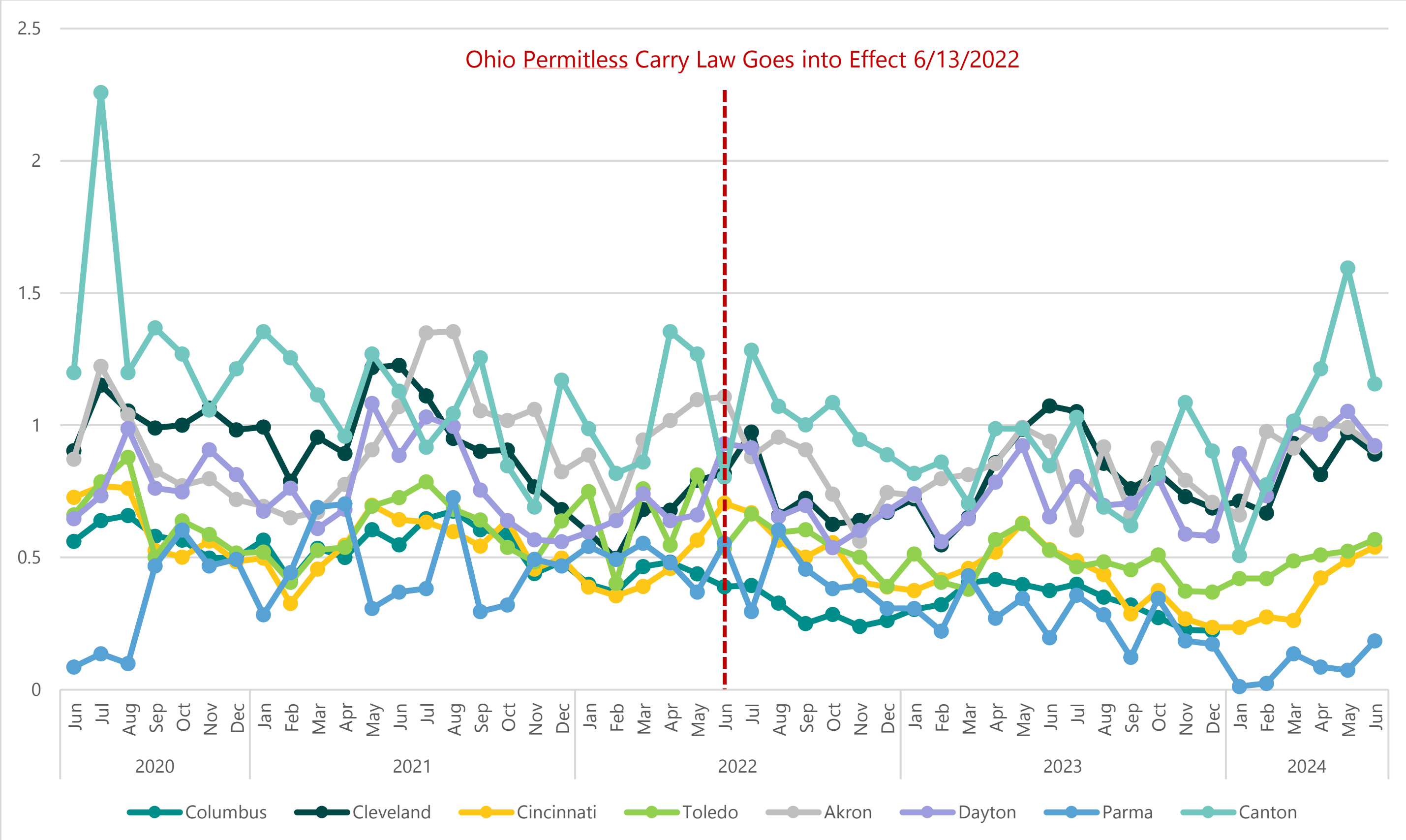


Figure 2. Michigan Incidents Involving a Firearm per 1,000 Persons.

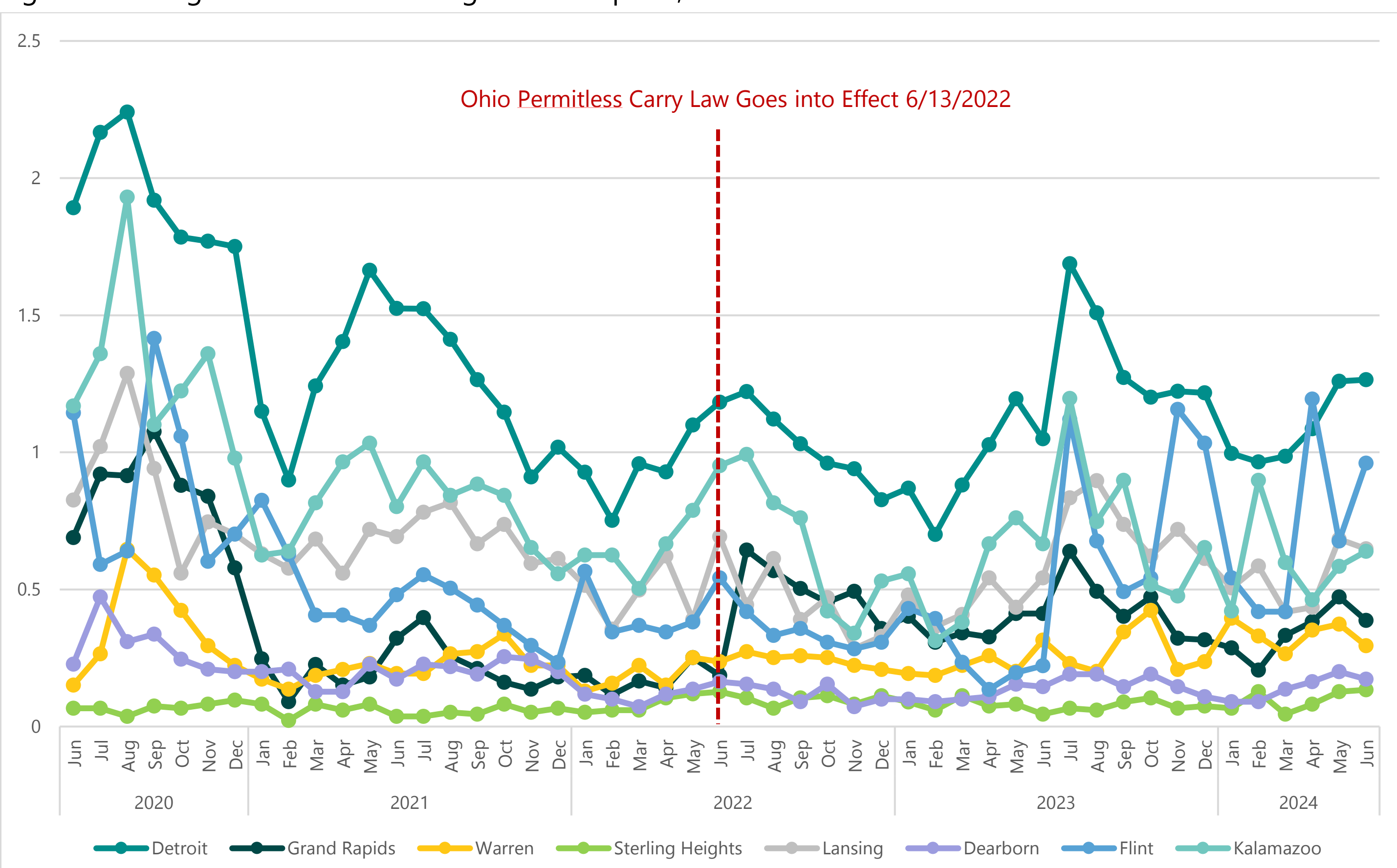
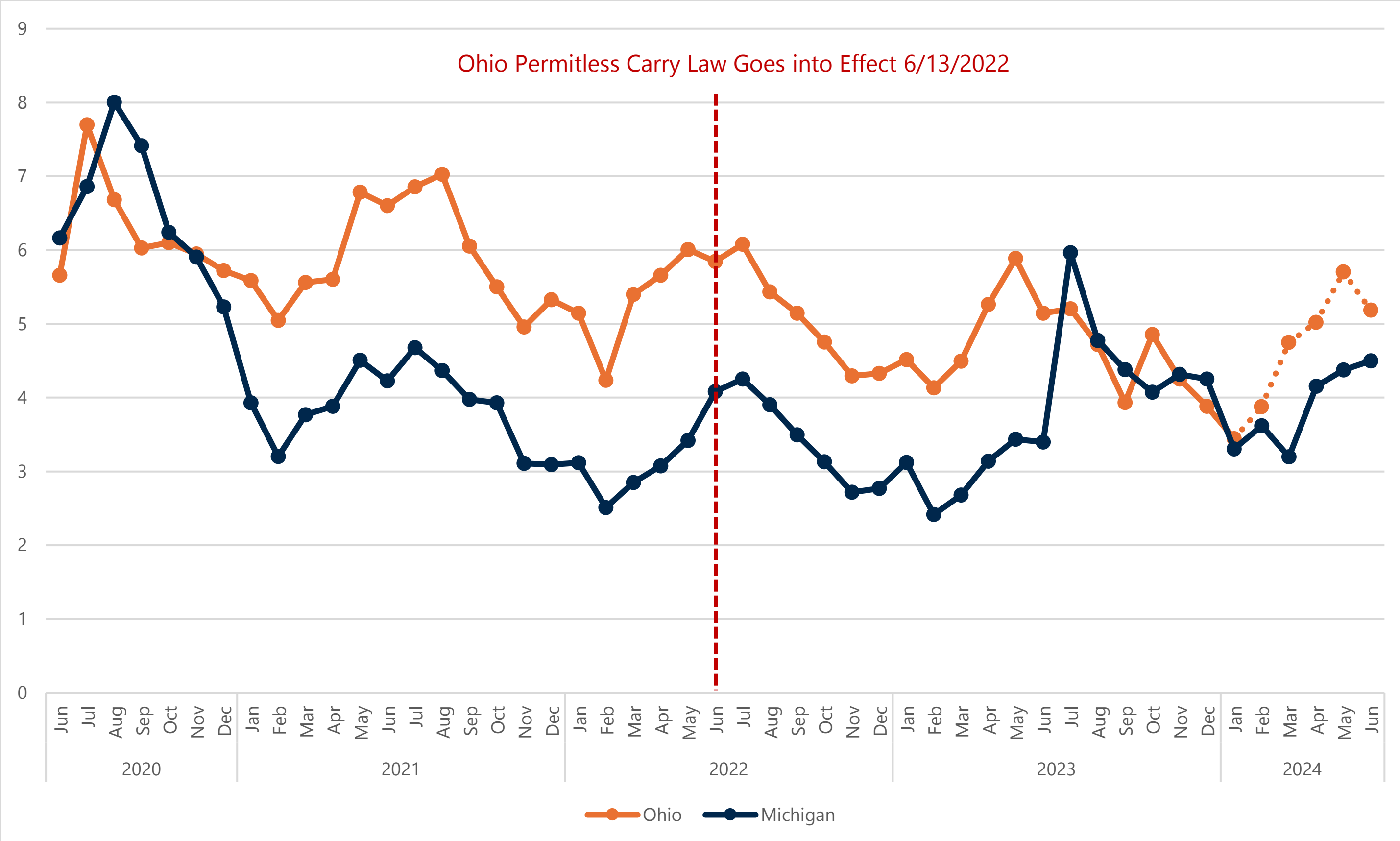
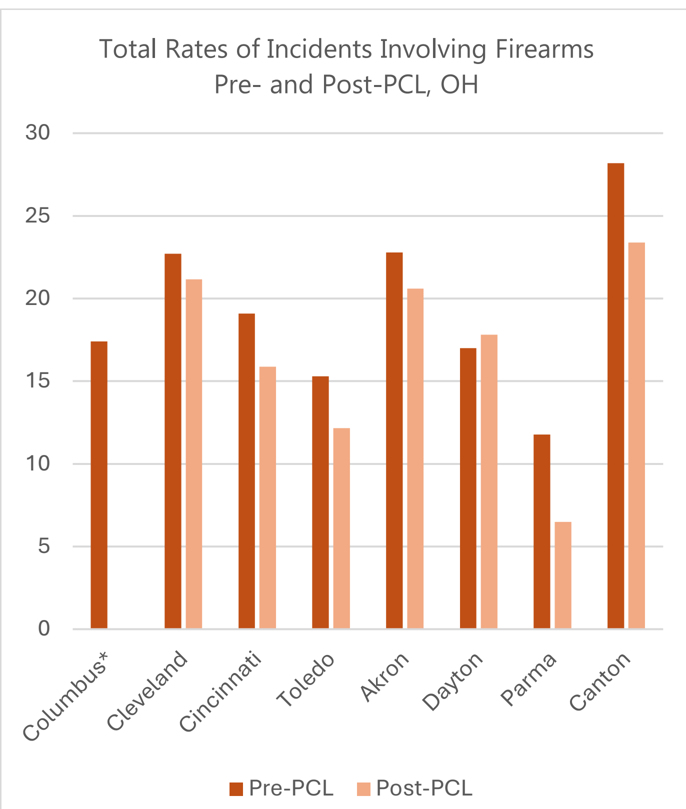


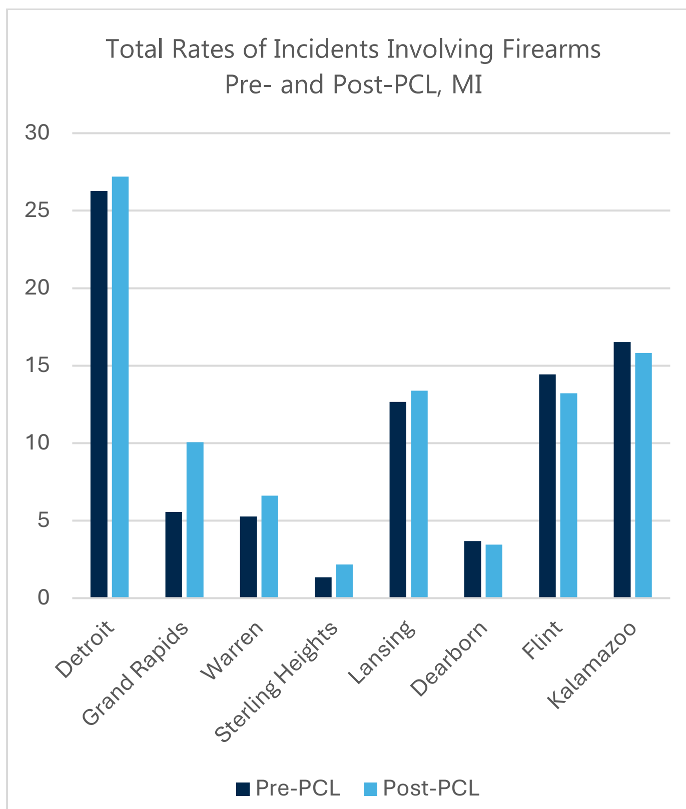
Figure 3. Total Rates of Incidents Involving Firearms Per 1,000 Persons, Select Cities in Ohio and Michigan.



*Dotted line indicates incomplete total as we do not yet have crime incident data from Columbus for 2024.

Figures 4 and 5. Total Rates of Incidents Involving Firearms Pre- and Post-PCL, OH and MI





Results

Two statistical methods were used to analyze the data from Ohio and Michigan. The Mann-Kendall Trend Test determined whether trends in firearm incidents were increasing or decreasing, and an Independent Samples T-Test compared the number of incidents before and after the passage of Ohio's Permitless Carry Law. These tests were run twice for Ohio, once with all eight cities from June 2020 through December 2023, and once from June 2020 to June 2024, excluding Columbus due to missing data.

Table 3. Ohio Statistical Results June 2020-December 2023

	Mann-Kendall Trend Test			Independent Samples T-Test		
City	tau	*p*-value	Sen's Slope	*t*-value	*df*	*p*-value
Columbus	**-0.45**	**0.001**	**-1.71**	**9.222**	**83.815**	**<.001**
Cleveland	**-0.27**	**0.001**	**-0.73**	**2.464**	**84**	**.016**
Cincinnati	**-0.19**	**0.015**	**-0.25**	**2.347**	**84**	**.021**
Toledo	**-0.22**	**0.001**	**-.029**	**4.092**	**82.343**	**<.001**
Akron	-0.03	0.675	-0.06	**2.135**	**83.483**	**.036**
Dayton	-0.15	0.051	-0.10	1.301	84	.197
Parma	-0.08	0.341	-0.04	**2.600**	**84**	**.011**
Canton	**-0.30**	**0.001**	**-0.21**	**3.009**	**84**	**.003**
All Cities Combined	**-0.33**	**0.001**	**-3.31**	**5.266**	**84**	**<.001**

As seen in the table above, the trends in every city and in all cities combined were decreasing. Most of these were significant, with the exception of Akron, Dayton, and Parma. The results of the t-test show that all datasets experienced significant variations before and after the PCL, aside from Dayton.

Table 4. Ohio Statistical Results June 2020-June 2024, Excluding Columbus

	Mann-Kendall Trend Test			Independent Samples T-Test		
City	tau	*p*-value	Sen's Slope	*t*-value	*df*	*p*-value
Cleveland	**-0.20**	**0.004**	**-0.44**	**2.408**	**96**	**.018**
Cincinnati	**-0.32**	**0.001**	**-.038**	**3.146**	**96**	**.002**
Toledo	**-0.32**	**0.001**	**-0.31**	**4.457**	**80.793**	**<.001**
Akron	-0.02	0.736	-0.03	1.705	87.523	.092
Dayton	-0.01	0.990	0.01	-.168	96	.867
Parma	**-0.31**	**0.001**	**-0.15**	**4.189**	**96**	**<.001**
Canton	**-0.22**	**0.002**	**-.013**	**2.552**	**96**	**.012**
All Cities Combined	**-0.27**	**0.001**	**-1.33**	**3.492**	**96**	**<.001**

When the study period was extended and Columbus excluded from the analysis, all cities combined and each city separately were decreasing. The Mann-Kendall test detected that these trends were significant except in Akron and Dayton. Similarly, results from the t-test indicated significant variation in the average numbers of pre- and post-PCL incidents in all cities combined and every city, apart from Akron and Dayton, .

Table 5. Michigan Statistical Results June 2020-June 2024

	Mann-Kendall Trend Test			Independent Samples T-Test		
City	tau	*p*-value	Sen's Slope	*t*-value	*df*	*p*-value
Detroit	**-0.28**	**0.001**	**-1.86**	**3.402**	**74.791**	**.001**
Grand Rapids	-0.01	0.97	0.001	-.547	60.924	.587
Warren	0.09	0.25	0.03	-.612	96	.542
Sterling Heights	**0.16**	**0.03**	**0.02**	**-2.951**	**96**	**.004**
Lansing	**-0.24**	**0.001**	**-0.15**	**3.178**	**96**	**.002**
Dearborn	**-0.32**	**0.001**	**-0.07**	**3.692**	**81.746**	**<.001**
Flint	-0.09	0.21	-0.05	.369	96	.713
Kalamazoo	**-0.34**	**0.001**	**-0.20**	**3.765**	**81.783**	**<.001**
All Cities Combined	**-0.25**	**0.001**	**-2.27**	**2.826**	**73.761**	**.006**

In Michigan, Mann-Kendall results revealed that while most cities experienced decreases in crime incidents involving firearms, Warren and Sterling Heights' incidents increased, with the latter being significant. In all cities combined and Detroit, Lansing, Dearborn, Kalamazoo decreased significantly. The t-test identified significant differences in these same cities, as well as in all cities combined with the addition of Sterling Heights, before and after the passage of Ohio's PCL.

Findings and Future Directions

This study found that firearm crime rates in both Ohio and Michigan followed similar seasonal patterns, with higher rates in spring and summer. However, these seasonal peaks have gone down each year. The Mann-Kendall trend test showed a clear decrease in firearm crimes in several Ohio cities—like Akron, Columbus, and Toledo—and across all eight Ohio cities combined. A similar decline was seen in most Michigan cities, including Detroit and Lansing. In contrast, Grand Rapids and Sterling Heights showed increases. The t-test also found significant changes in the average number of firearm incidents before and after the PCL in several cities from both states.

In the future, we plan to expand the study period to better understand long-term changes. Adding more cities from both PCL and non-PCL states could also improve the analysis. Future research might also consider other factors that might affect firearm crime, like local policies, economic conditions, or police activity.