Canada's Battle Against Car Theft: Progress Amid Persistent Challenges*

Government measures and public vigilance show promise, but organized theft networks remain a concern.

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Vehicle theft has become a significant public concern in Canada, highlighting both systemic challenges and promising governmental interventions. This study evaluates the effectiveness of the 2024 National Action Plan, which led to a 16.9% reduction in the mean monthly count of car thefts in Toronto. Spatial and temporal analyses reveal variations across police divisions and premise types, emphasizing the need for targeted strategies. Despite encouraging trends, organized theft networks and data limitations underscore the need for further research and adaptive policymaking.

*Code and data are available at: https://github.com/vanessadyy/Car_Theft.

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1 Introduction

Vehicle theft has become a widespread public concern in Canada, leaving many citizens feeling helpless and frustrated. As car theft incidents continue to rise, police chiefs have made surprising recommendations, including advising residents to leave their car keys near the door to avoid violent confrontations during break-ins. This suggestion sparked public outrage, with many criticizing it online as absurd and unreasonable. The widespread public discourse escalated the issue into a national battle against crime.

1.1 The Scale of the Problem

The scale of vehicle theft in Canada is alarming, exposing government inefficiency in tackling the problem. The reaction from law enforcement has been equally unexpected, with officers treating theft as an inevitable occurrence and even providing rationales for its prevalence. While insurance companies offer quick resolutions for stolen vehicle claims, this comes at a cost. Insurers are not charitable organizations, and frequent claims could lead to higher premiums or even the loss of insurance eligibility for some car owners. The reliance on insurance as a remedy highlights the authorities' decision to abandon pursuit of stolen vehicles, shifting the burden onto vehicle owners to seek reimbursement.

1.2 The Vicious Cycle of Vehicle Theft

The indifferent attitude of law enforcement, coupled with lenient legal consequences, has fueled an annual increase in car thefts, pushing Canada into a vicious cycle of buying and stealing vehicles. The legal responsibilities surrounding car theft and the evasive accountability of international import companies reflect the complexities of organized crime. A large portion of stolen vehicles ends up in the Middle East and Africa, particularly Nigeria, where demand for high-quality second-hand cars is strong. The COVID-19 pandemic and geopolitical conflicts have exacerbated supply shortages, causing car prices in the Middle East to surge and further incentivizing theft.

1.3 The Global Supply Chain of Stolen Vehicles

The vehicle theft industry operates as an international supply chain, where cars of varying quality are allocated to different markets, creating a clear hierarchy. High-value vehicles are often shipped to affluent buyers, while lower-tier models serve other regions. The organized and systematic nature of these operations underscores the challenges faced by Canadian authorities in addressing this growing issue. Without comprehensive legal reforms and stricter enforcement measures, the country risks further entrenchment in this illicit cycle, with profound economic and social consequences.

1.4 Public Response and Anti-Theft Measures

Faced with insufficient responses from the police, many vehicle owners have begun implementing their own anti-theft measures. However, professional thieves often view these devices as minor obstacles, and even robust anti-theft systems have limitations. High installation costs and vulnerabilities in extreme weather conditions further undermine their effectiveness. Some individuals attempt to protect their vehicles by parking in neighborhoods with higher police presence or near police stations. However, such measures do not guarantee safety, as evidenced by reports of police chiefs' vehicles being stolen in broad daylight. These incidents highlight the audacity of thieves and have led to online ridicule of police authorities for failing to practice basic precautions.

1.5 The National Action Plan

Under pressure from the public and media, the Canadian government introduced a series of policies in early 2024 as part of a "National Action Plan" to combat auto theft. The key components of the plan include:

- **Amendments to Criminal Laws**: Revising legislation to provide law enforcement and prosecutors with enhanced tools to tackle vehicle theft.
- **Changes to the Radiocommunication Act**: Tightening regulations on radio devices commonly used in car thefts.
- **Enhanced Intelligence and Information Sharing**: Promoting better collaboration among municipal, provincial, federal, and international agencies.
- **Technology Deployment**: Leveraging advanced technologies such as scanning systems, data analytics, and GPS tracking to enhance inspection efficiency, particularly at ports and rail terminals.
- **Specialized Training**: Offering targeted training programs for law enforcement officers to improve their capacity to investigate vehicle theft cases.
- **Intergovernmental Task Force**: Creating a National Vehicle Theft Task Force to enhance coordination among government bodies.
- **Support for Anti-Theft Technology Development**: Encouraging innovation and wider adoption of commercial anti-theft technologies.

1.6 Interim Result and Aim of the Paper

Several months have passed since the plan's implementation. Open Data Toronto has published theft-from-motor-vehicle data for Toronto reported from January 2014 to September 2024. To assess interim results, we analyzed this dataset to evaluate the effectiveness of the government's actions. Our objective is to produce statistically objective conclusions that quantify the plan's impact.

1.7 Estimand

The primary estimand of this study is the monthly reduction in mean counts of car theft cases in Toronto following the implementation of the National Action Plan. This is defined as the difference in the mean monthly car theft count before and after January 2024, when the plan starts. The estimand will be evaluated across all vehicle theft records reported in Toronto, stratified by key covariates. This analysis assumes that the observed trends are not confounded by unrelated temporal factors.

2 Data

Since 2014, the Toronto Police Service has been collecting auto theft data in digital format. The data is updated and maintained quarterly, with public access provided via Open Data Toronto. This dataset includes approximate locations of car theft incidents, facilitating the analysis of geographic trends over time. The latest update, released on October 19, 2024, covers reported theft cases up to September 30, 2024.

2.1 Data Source

The dataset used in this study was obtained from Open Data Toronto. The raw dataset comprises the following key fields:

Table 1: Raw Variable Description

Column	Description
X_id	Unique row identifier for Open Data database
EVENT_UNIQUE_ID	Offence Number
REPORT_DATE	Date Offence was Reported
OCC_DATE	Date of Offence
REPORT_YEAR	Year Offence was Reported
REPORT_MONTH	Month Offence was Reported
REPORT_DAY	Day of the Month Offence was Reported
REPORT_DOY	Day of the Year Offence was Reported
REPORT_DOW	Day of the Week Offence was Reported
REPORT_HOUR	Hour Offence was Reported
OCC_YEAR	Year Offence Occurred
OCC_MONTH	Month Offence Occurred
OCC_DAY	Day of the Month Offence Occurred
OCC_DOY	Day of the Year Offence Occurred

OCC_DOW	Day of the Week Offence Occurred
OCC_HOUR	Hour Offence Occurred
DIVISION	Police Division where Offence Occurred
LOCATION_TYPE	Location Type of Offence
PREMISES_TYPE	premise types of Offence
UCR_CODE	UCR Code for Offence
UCR_EXT	UCR Extension for Offence
OFFENCE	Title of Offence
MCI_CATEGORY	MCI Category of Occurrence
HOOD_158	Identifier of Neighbourhood using City of Toronto's new 158 neighbourhood structure
LONG_WGS84	Longitude coordinate
LAT_WGS84	Latitude coordinate

2.2 Data Notes

This dataset provides detailed information about auto theft cases reported in Toronto. Each row corresponds to a unique occurrence and includes both temporal and spatial details about the offence. The data can be used to analyze trends over time and across neighborhoods in the city.

- **Temporal Variables**: Columns such as `REPORT_DATE`, `REPORT_YEAR`, and `OCC_DATE` provide insights into when offences were reported or occurred.
- **Spatial Variables**: Columns like `DIVISION`, `HOOD_158`, `LONG_WGS84`, and `LAT_WGS84` enable spatial analysis and visualization of offences across Toronto.
- **Categorical Variables**: Fields such as `LOCATION_TYPE`, `PREMISES_TYPE`, and `OFFENCE` classify the nature and context of the reported incidents.

2.3 Variables of Interest

Dependent or duplicated information was recorded using different variables in the dataset. To avoid redundancy, for each scenario, we selected representative variables from the categories of temporal, spatial, and crime severity information related to theft crimes. The selected variables are outlined below:

- **Temporal Information** We selected variables representing the occurrence date and excluded the reported date. The following variables were retained for analysis:
  - OCC_DATE
  - OCC_YEAR

- OCC_MONTH
- OCC_DAY
- OCC_DOW
- OCC_HOUR

- **Spatial Information** Key spatial information is represented by the police division number, as well as the longitude and latitude of the theft location. Additionally, the location type was included for further context. The following variables were retained:
  - DIVISION
  - LONG_WGS84
  - LAT_WGS84
  - PREMISES_TYPE

- **Crime Severity Information** To capture the severity of theft crimes, we selected the UCR code and offense title as indicators. The following variables were retained:
  - UCR_CODE
  - OFFENCE

2.4 Software and Packages

We used R 4.3 for analysis and followed a public template R Core Team (2023)Alexander (2023), and a collection of R packages were used in this study:

- tidyverse Wickham et al. (2019)
- here Müller (2020)
- lubridate Grolemund & Wickham (2011)
- ggplot2 Wickham (2016)
- scales Wickham, Pedersen, & Seidel (2023)
- knitr Xie (2024)
- kableExtra Zhu (2024)
- topmodels Zeileis, Lang, & Stauffer (2024)
- distributions3 Hayes et al. (2024)
- MASS Venables & Ripley (2002)
- sf Pebesma (2018)
- rstudioapi Ushey, Allaire, Wickham, & Ritchie (2024)
- opendatatoronto Gelfand (2022)
- janitor Firke (2023)

2.5 Data Management

Data cleaning steps are described in the Appendix. A sample set of the cleaned data is presented in Table 2-4. Among all variables, Year, Total_Death, Male, and Female are coded as integers, Month is coded as abbreviations in character format, and Time is coded in date format. After data cleaning, there are no missing values remaining in the dataset.

Table 2: Sample of Clean Data: Part 1

X_id	OCC_DATE	OCC_YEAR	OCC_MONTH	OCC_DAY	OCC_DOW
1	2014-01-01	2014	January	1	Wednesday
3	2014-01-01	2014	January	1	Wednesday
15	2014-01-01	2014	January	1	Wednesday
16	2014-01-01	2014	January	1	Wednesday
18	2014-01-01	2014	January	1	Wednesday
19	2014-01-01	2014	January	1	Wednesday

Table 3: Sample of Clean Data: Part 2

OCC_HOUR	DIVISION	PREMISES_TYPE	UCR_CODE
8	D51	House	2142
11	D42	House	2142
0	D14	Outside	2142
1	D23	House	2142
3	D14	Outside	2142
1	D51	Commercial	2142

Table 4: Sample of Clean Data: Part 3

OFFENCE	LONG_WGS84	LAT_WGS84
Theft From Motor Vehicle Under	-79.37453	43.65707
Theft From Motor Vehicle Under	-79.27716	43.81731
Theft From Motor Vehicle Under	-79.40111	43.65227
Theft From Motor Vehicle Under	-79.56457	43.71941
Theft From Motor Vehicle Under	-79.41877	43.65445
Theft From Motor Vehicle Under	-79.37524	43.64635

3 Methods

3.1 Poisson Regression

The Poisson distribution is utilized to model the monthly count of car thefts, with a binary variable “action” serving as an indicator of whether the time of theft occurrence falls after the implementation of the national action plan. The following are the formulas for the Poisson regression model:

$$y_i \sim \text{Poisson}(\lambda_i)$$

$$\log(\lambda_i) = \beta_0 + \beta_1 \cdot \text{time} + \beta_2 \cdot \text{action} + \cdots + \beta_k \cdot \text{covariate}_k$$

where y_i is the count of car theft occurance.

We ran a generalized linear model with a log link function, ensuring that all of the predicted values will be positive, and using a Poisson error distribution.

3.2 Quasi-likelihood Poisson Regression

To address the potential for overdispersion, we also performed a quasi-likelihood Poisson regression. This approach uses the same mean function as standard Poisson regression but estimates parameters using quasi-maximum likelihood estimation or generalized estimating equations, with adjustments for an estimated dispersion parameter. We compared the results from Poisson and Quasi-Poisson regression models, selecting the more suitable model based on a comprehensive diagnostic evaluation. This assessment included checks for overdispersion, identification of outliers, and analysis of residual distribution. Further details are provided in the [results section]{Section 4}.

4 Results

4.1 Descriptives

Before running the model, we firstly draw a few figures and tables as descriptives to have a quickview of the data.

4.1.1 Timely Trend (Quarterly)

Figure 1 illustrates the overall trend in the quarterly count of car theft cases in Toronto since 2014. The number of cases generally fluctuated around 2,000 per quarter. Notable periods of lower counts include 2016 and the first two quarters of 2021, while higher counts were observed during 2020 and the period from 2022 to 2023. A decline is also apparent after 2024, though further evidence is needed to confirm this trend.

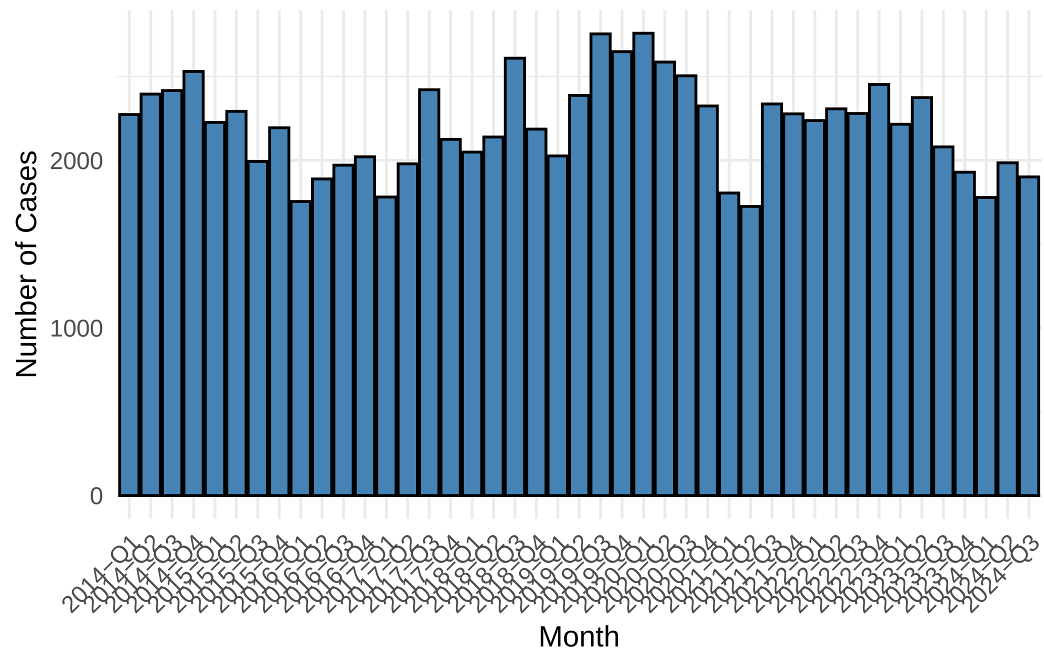

Figure 1: Histogram of quarterly count of car theft in Toronto

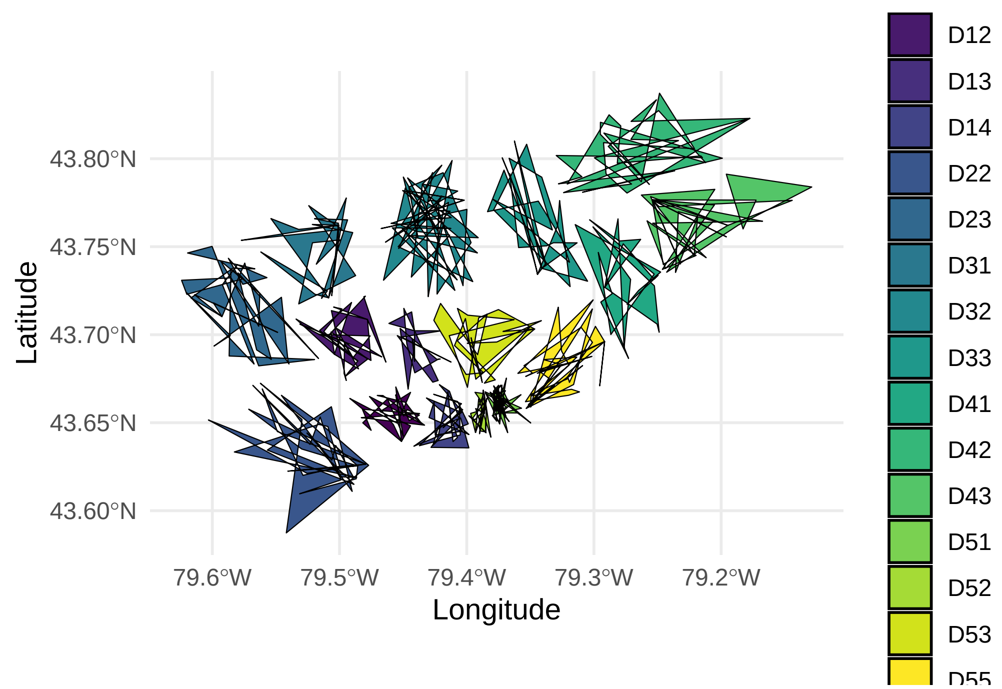

Figure 2: Spatial view of vehicle theft cases by division for September 2024

4.1.2 Spatial View

Figure 2 illustrates the spatial distribution of car theft occurrences in September 2024 across police divisions. Figure 3 displays the overall count of car theft cases by division. Notably, Division D54 reported the lowest number of car theft cases, with Divisions D11 to D13 also showing relatively low counts, while Division D33 recorded the highest. Further analysis is needed, considering additional information about public safety conditions within these division areas.

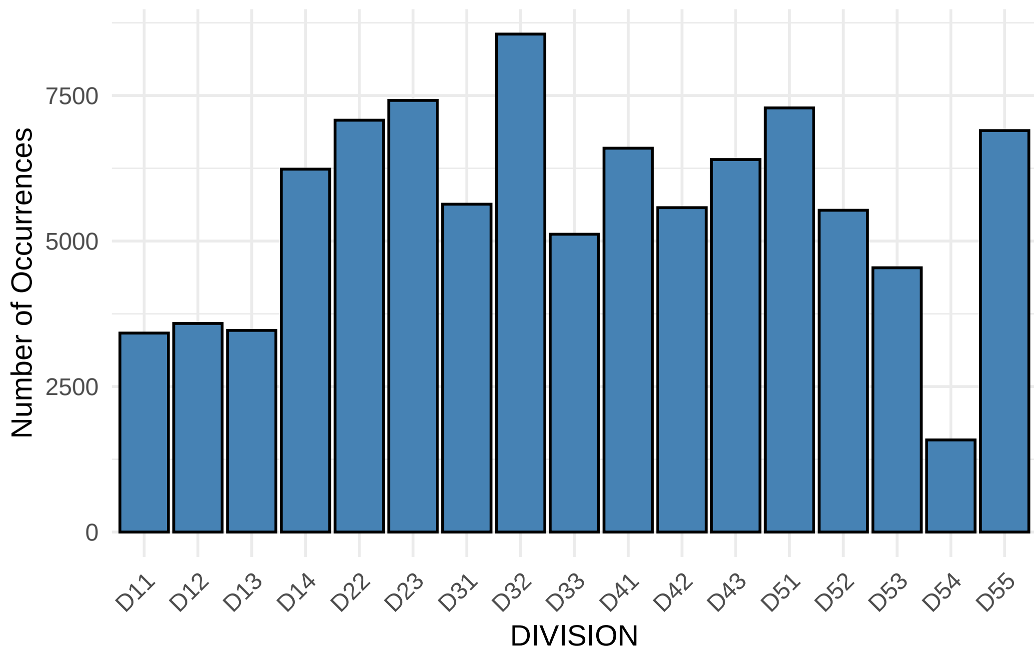

Figure 3: Barchart of count of occurrences by divisions

4.1.3 Premise Types

Figure 4 reveals that car theft cases occurred most frequently outside, followed by educational institutions, while transit locations reported the fewest cases. Across all premise types, two periods of increase were observed in 2019 and 2022-2023, with a decline noted after 2024.

4.1.4 Offence Types

Figure 5 shows that most car theft cases were categorized as “Theft From Motor Vehicle Under,” involving financial losses of less than $5,000. The number of severe cases remained

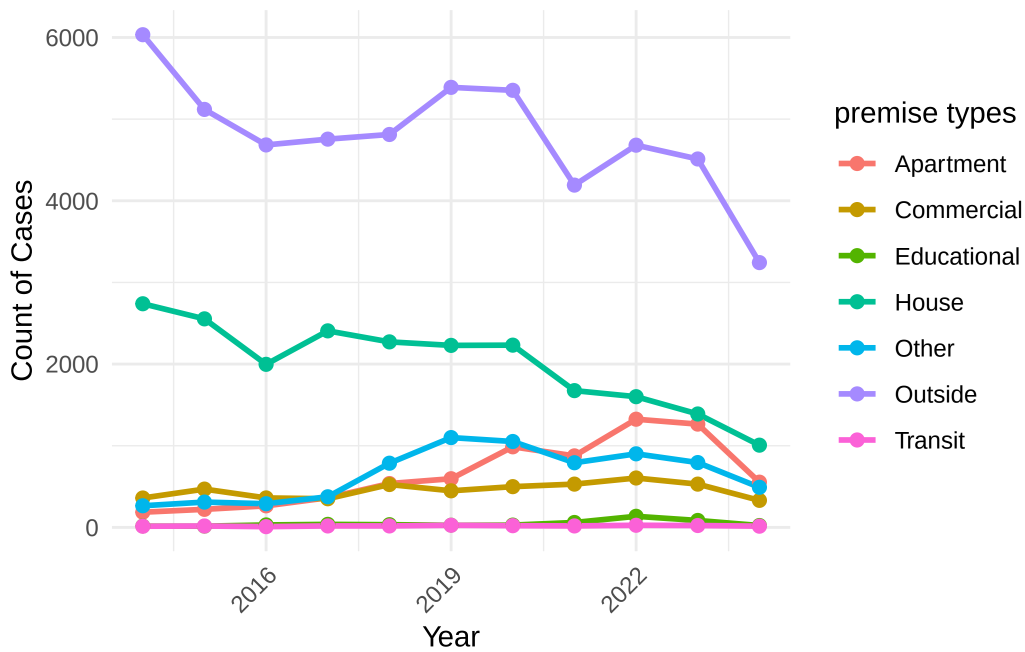

Figure 4: Linechart of count of occurrences by premise types and year

relatively stable over the years, while lighter cases experienced two increases in 2019 and 2022, with declines observed in 2016 and after 2024.

4.1.5 Day of the Week

Figure 6 indicates that car theft crimes were distributed relatively evenly across all days of the week, with a slight increase observed on Fridays.

4.1.6 Day of the Month

Interestingly, Figure 7 reveals that car theft cases occurred most frequently on the first day of the month and least often at the end of the month. The difference could be as high as 1,000 cases over a 10-year period, equivalent to approximately 30%.

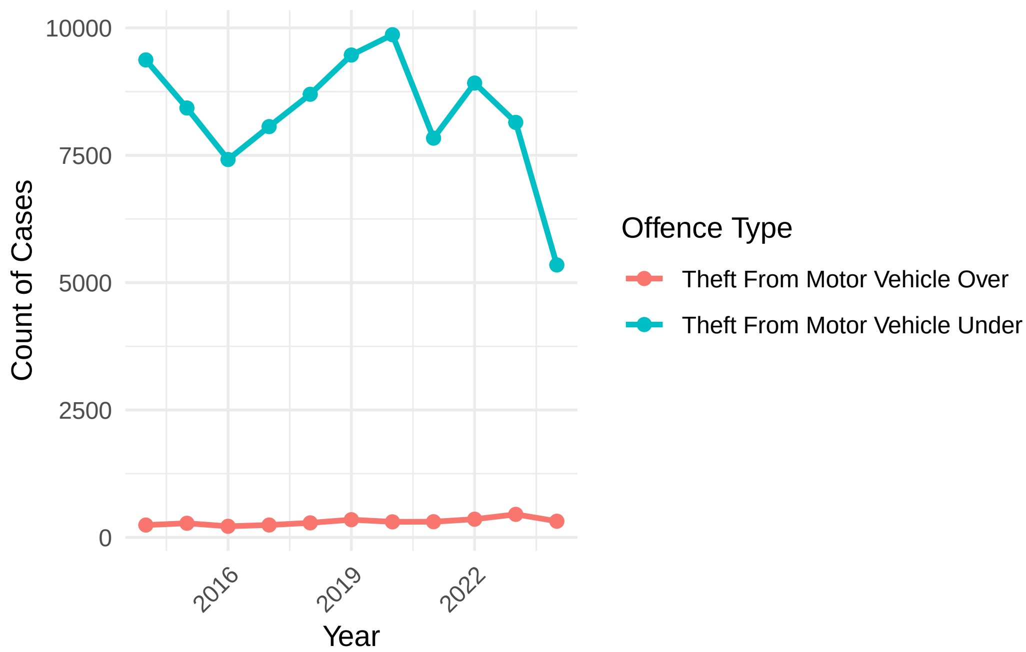

Figure 5: Linechart of count of occurrences by offence types and year

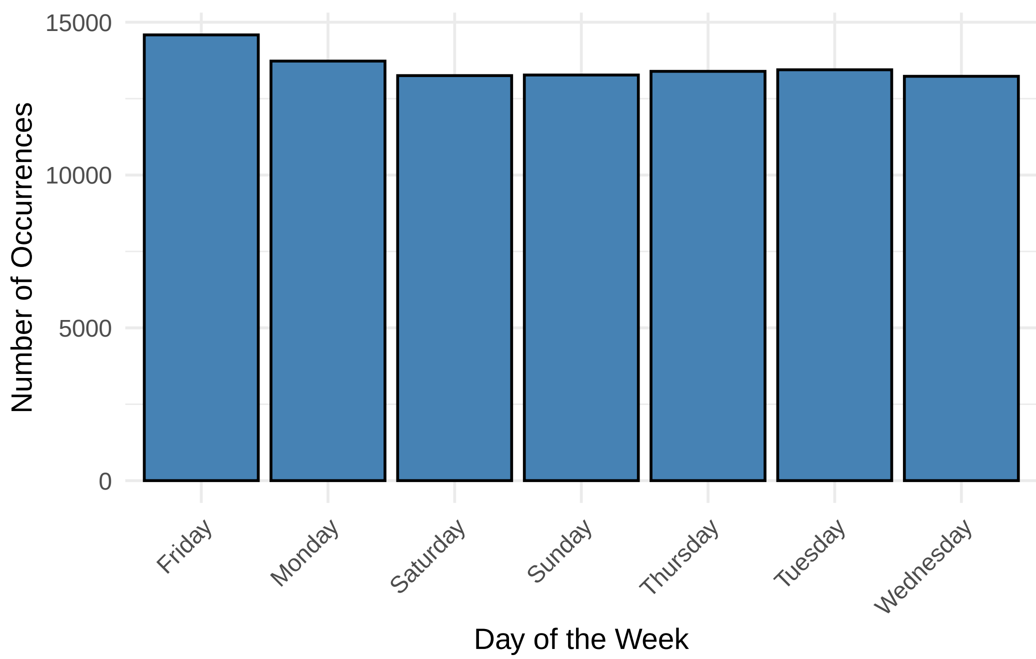

Figure 6: Barchart of count of occurrences by day of the week

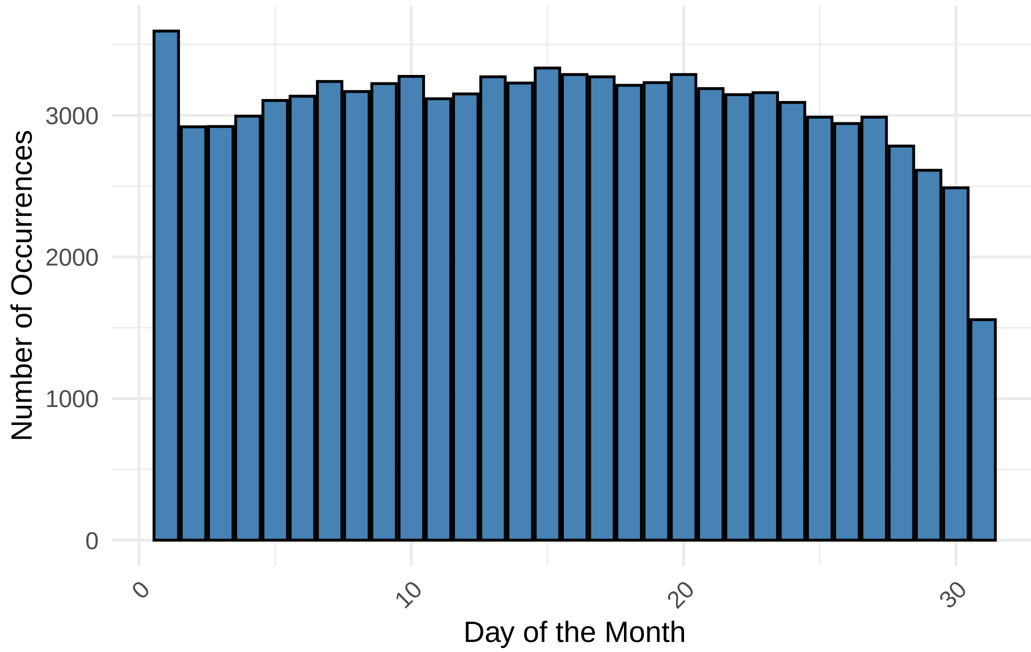

Figure 7: Barchart of count of occurrences by day of the month

4.2 Poisson Model

4.2.1 Point Estimates

Table 5 indicates that the variable "action" had a significant effect on the mean count of car theft cases. Specifically, after the implementation of the national action plan, there was an approximate $1-\exp(-0.185)=1-0.831=16.9\%$ reduction in the mean count of car theft cases. This result highlights the potential effectiveness of the action plan in mitigating car theft, suggesting a notable decrease in incidents following its introduction.

Table 5: Poisson regression results

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	6.4422634	0.0568944	113.231977	0.0000000
time	0.0000095	0.0000032	2.983433	0.0028503
action	-0.1855441	0.0150397	-12.336996	0.0000000

4.2.2 Prediction

Predictions from the model in Figure 8 demonstrate a significant difference in the expected monthly car theft counts, with post-2024 counts being approximately 100 cases lower per month on average. This reduction suggests a measurable impact of national action plan starting in 2024.

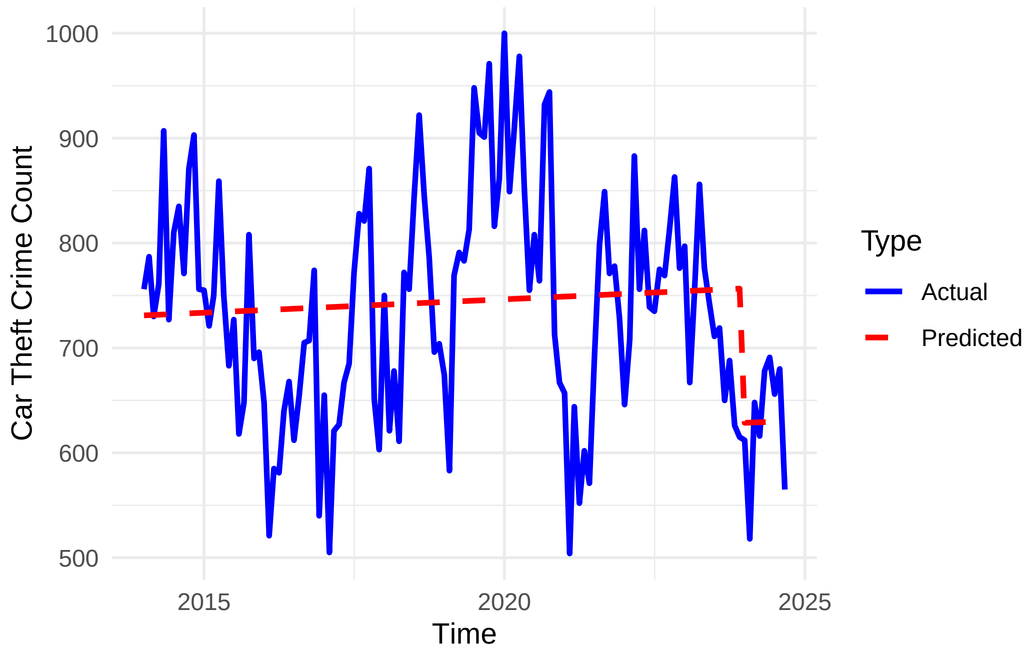

Figure 8: Poisson regression prediction

4.2.3 Model Diagnosis

The dispersion factor from Table 6 is 14.74, indicating significant overdispersion in the data. The rootogram in Figure 9 reveals overfitting for crime counts in the range of 700–800 and underfitting for other ranges. Diagnostic plots in Figure 10 show no major deflation in the QQ plot, suggesting a normal distribution of residuals. Leverage plots indicate only three significant outliers, corresponding to observations 5, 26, and 122.

Table 6: Poisson regression dispersion factor

Stats	Value
Dispersion Factor	14.73955

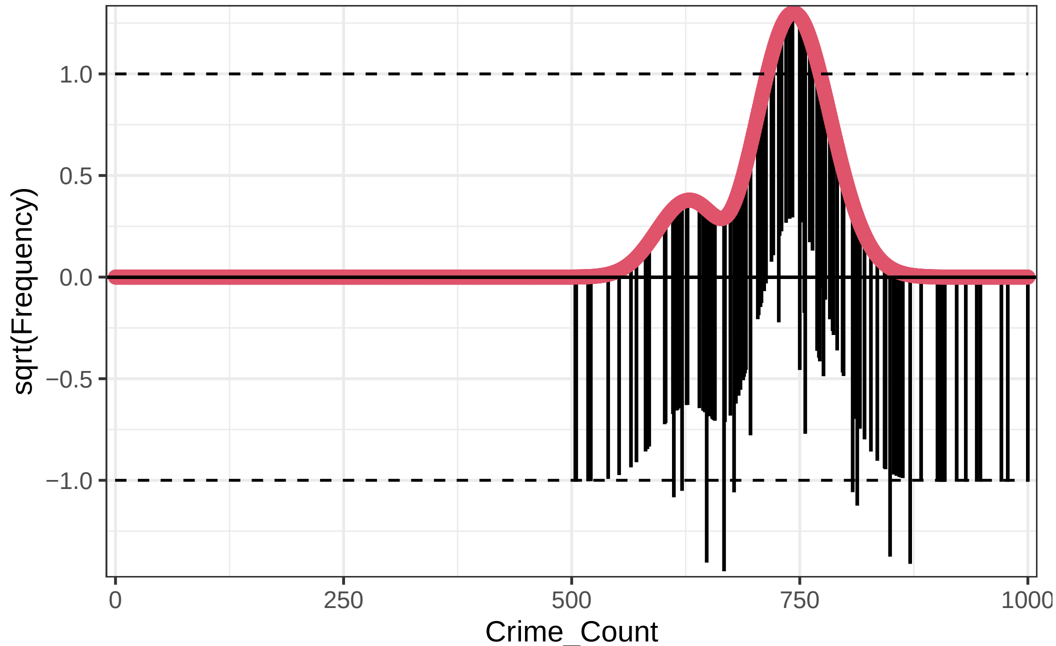

Figure 9: Poisson regression rootogram

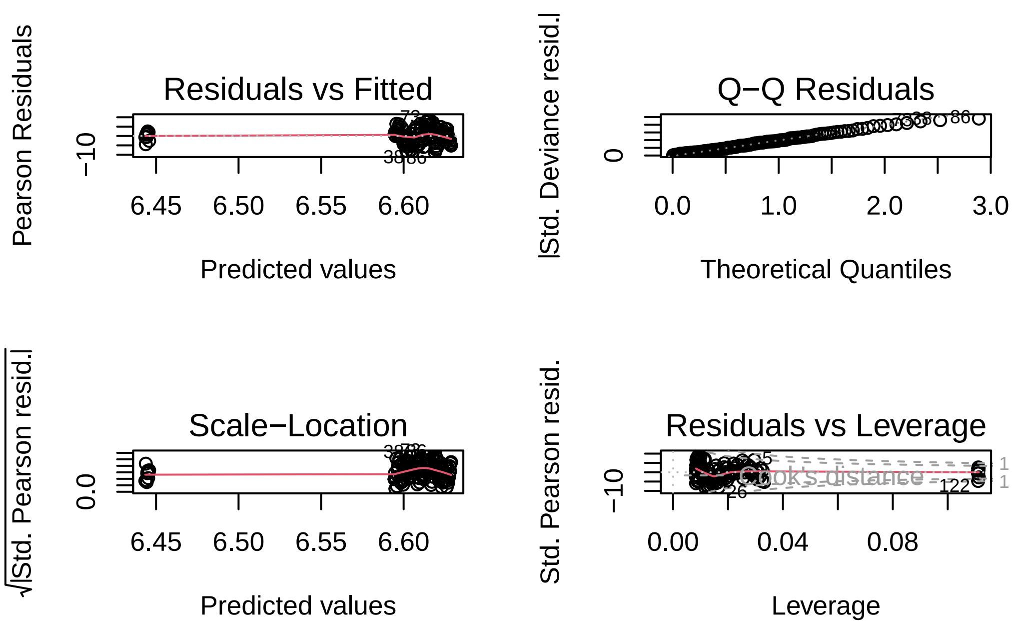

Figure 10: Poisson regression model diagnosis

4.3 Quasi-Poisson Model

Table 7 shows that the Quasi-Poisson model produced the same point estimate for the effect of "action," indicating a 16.9% reduction in the mean count of car theft cases following the implementation of the national action plan. However, the Quasi-Poisson model estimated a larger standard error, resulting in narrower confidence intervals (see Table 7), which may provide a more reliable and appropriate measure of precision.

Table 7: Quasi-likelihood Poisson regression results

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	6.4422634	0.2184296	29.4935438	0.0000000
time	0.0000095	0.0000122	0.7770951	0.4385592
action	-0.1855441	0.0577404	-3.2134185	0.0016657

Table 8: Comparison between Quasi-likelihood Poisson and Poisson estimated confidence intervals

	2.5 %	97.5 %	model_type
(Intercept)	6.3307293	6.5537516	Poisson Model
time	0.0000032	0.0000157	Poisson Model
action	-0.2151063	-0.1561508	Poisson Model
(Intercept)1	6.0137971	6.8700524	Quasi-Poisson Model
time1	-0.0000144	0.0000334	Quasi-Poisson Model
action1	-0.2999883	-0.0735884	Quasi-Poisson Model

4.4 Model with covariates

Table 9: Quasi-likelihood Poisson regression with covariate of premise types

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	3.8692036	0.1853514	20.8749597	0.0000000
time	0.0000089	0.0000101	0.8824230	0.3777979
PREMISES_TYPECommercial	-0.3592271	0.0588228	-6.1069365	0.0000000
PREMISES_TYPEEducational	-2.5681776	0.1491690	-17.2165638	0.0000000
PREMISES_TYPEHouse	1.1252047	0.0434094	25.9207406	0.0000000
PREMISES_TYPEOther	-0.0025122	0.0533743	-0.0470679	0.9624702
PREMISES_TYPEOutside	1.9955553	0.0401996	49.6412099	0.0000000
PREMISES_TYPETransit	-3.2777835	0.2262940	-14.4846221	0.0000000

Table 9: Quasi-likelihood Poisson regression with covariate of premise types

	Estimate	Std. Error	t value	Pr(>|t|)
action	-0.1859329	0.0480472	-3.8697965	0.0001173

Table 10: Quasi-likelihood Poisson regression with covariate of offence types

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	3.0982947	0.1752579	17.678486	0.0000000
time	0.0000095	0.0000094	1.010682	0.3131304
OFFENCETheft From Motor Vehicle Under	3.3080341	0.0519257	63.707104	0.0000000
action	-0.1855441	0.0443956	-4.179340	0.0000403

Table 11: Quasi-likelihood Poisson regression with covariate of divisions

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	2.8242025	0.1359040	20.7808661	0.0000000
time	0.0000259	0.0000073	3.5571310	0.0003832
DIVISIOND12	0.0471314	0.0543520	0.8671511	0.3859583
DIVISIOND13	0.0133645	0.0548057	0.2438526	0.8073688
DIVISIOND14	0.6008305	0.0483830	12.4182190	0.0000000
DIVISIOND22	0.7273607	0.0473538	15.3601393	0.0000000
DIVISIOND23	0.7742917	0.0469988	16.4747058	0.0000000
DIVISIOND31	0.4992940	0.0492901	10.1297014	0.0000000
DIVISIOND32	0.9172847	0.0460002	19.9408877	0.0000000
DIVISIOND33	0.4032202	0.0502200	8.0290750	0.0000000
DIVISIOND41	0.6569637	0.0479130	13.7115829	0.0000000
DIVISIOND42	0.4887648	0.0493885	9.8963217	0.0000000
DIVISIOND43	0.6271061	0.0481603	13.0212259	0.0000000
DIVISIOND51	0.7568810	0.0471289	16.0598224	0.0000000
DIVISIOND52	0.4806589	0.0494648	9.7171968	0.0000000
DIVISIOND53	0.2837991	0.0514799	5.5128094	0.0000000
DIVISIOND54	0.1173625	0.0695454	1.6875670	0.0916429
DIVISIOND55	0.7018834	0.0475524	14.7602203	0.0000000
action	-0.1995083	0.0341973	-5.8340430	0.0000000

Table 9, Table 10, and Table 11 present point estimates from models incorporating different covariates. The results indicate that parking outside significantly increases the risk of car theft occurrences. Additionally, theft categorized as “Theft From Motor Vehicle Under” was associated with a higher number of car theft cases. Among the divisions, Division 32 exhibited the highest risk of car theft occurrence.

5 Discussion

5.1 Impact of the National Action Plan

The results of this study indicate that the National Action Plan implemented in early 2024 has shown a measurable impact on reducing car theft in Toronto. Our analysis demonstrates a 16.9% reduction in the mean count of car theft cases after the action plan’s introduction, as evidenced by both Poisson and Quasi-Poisson regression models. This decline is further supported by the observed decrease in monthly crime counts after 2024, with an average reduction of 100 cases per month. These findings highlight the potential effectiveness of government-led initiatives in curbing auto theft, although additional time is needed to assess the plan’s long-term impact comprehensively.

5.2 Spatial and Temporal Patterns of Car Theft

The spatial analysis revealed substantial variation in car theft occurrences across police divisions. Division 32 consistently exhibited the highest risk of car theft, while Divisions 11, 12, 13, and 54 reported the lowest counts. These patterns may reflect underlying differences in socioeconomic conditions, policing strategies, or community vigilance within these divisions. Additionally, the analysis of premise types indicated that thefts occurred most frequently in outdoor locations, suggesting that vehicle owners parking outside face higher risks. Temporal trends revealed spikes in crime during certain years, notably 2019 and 2022–2023, followed by a decline in 2024. Interestingly, car thefts were most common at the beginning of the month, possibly linked to behavioral or logistical patterns among offenders.

5.3 Effectiveness of the National Action Plan

While the National Action Plan appears to have contributed to a decline in car theft cases, its effectiveness likely varies by division and offense type. The reduction in “Theft From Motor Vehicle Under” cases aligns with the broader trend but raises questions about whether certain measures disproportionately target less severe crimes. Furthermore, the use of enhanced technologies and intelligence sharing could be more impactful in divisions with historically higher crime rates, such as Division 32. These findings underscore the importance of tailoring interventions to the specific needs and challenges of different regions.

5.4 Weaknesses and Limitations

This study has several limitations. First, the data used were limited to reported cases, potentially underestimating the true extent of car theft due to unreported incidents. Second, the overdispersion identified in the Poisson model suggests variability that may not have been fully captured by the predictors included in our analysis. Although the Quasi-Poisson model provided more appropriate standard error estimates, additional covariates, such as socioeconomic factors or policing intensity, could further improve model accuracy. Lastly, the relatively short timeframe since the National Action Plan's implementation restricts our ability to evaluate its sustained effects.

5.5 Recommendations and Future Work

Based on the findings, we recommend that policymakers focus on areas with persistently high car theft rates, such as Division 32, to deploy targeted interventions. Efforts to improve public awareness of high-risk premise types, such as outdoor parking, could also reduce theft occurrences. Further research should explore the role of socioeconomic and environmental factors in shaping car theft trends, leveraging longer-term data to evaluate the sustained effectiveness of the National Action Plan. Additionally, integrating machine learning approaches could enhance predictive modeling and offer more granular insights into crime dynamics.

Appendix

Data Cleaning Steps

Raw data from Open Data Toronto were prepared, so we did not need to perform many cleaning steps. A few cleaning steps are as follows:

- Only variables of interest were kept.
- All records with all types of missing were excluded.
- Only record indicating car theft cases occurrence after 2014 were kept.

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