Fight Against Car Theft: Progress and Challenges*

A Data-Driven Review of the National Action Plan

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Car theft remains a pressing public safety concern in Canada, prompting a national response through the 2024 National Action Plan. This study uses Toronto as a case example to evaluate the plan's effectiveness, reporting a 16.93% reduction in the average monthly car theft count. Spatial and temporal analyses reveal notable disparities across areas covered by different police divisions and property types, highlighting the need for tailored local interventions. While the overall decline is encouraging, persistent challenges such as organized theft rings and data limitations underscore the necessity for continued research and adaptive policy development.

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

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1 Introduction

Car 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[1]. This suggestion sparked public outrage, with many criticizing it online as absurd and unreasonable[2]. The widespread public discourse escalated the issue into a national battle against crime.

1.1 The Scale of the Problem

The scale of car theft in Canada is alarming, exposing government inefficiency in tackling the problem. In 2023, the number of motor vehicle thefts in Canada increased by 8.44% compared to the previous year, totaling 114,863 incidents[3]. 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[4]. 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 Global Demand

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[5]. A large portion of stolen vehicles ends up in the Middle East and Africa, particularly Nigeria, where demand for high-quality used 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 International Supply Chain

The car theft industry functions as a global supply chain, allocating vehicles of varying quality to different markets, forming a clear hierarchy. High-value cars are often shipped to wealthy buyers, while lower-tier models are directed to less affluent regions. Locally stolen vehicles are transported to seaports, illegally smuggled through shipping containers, and delivered to buyers worldwide. The organized and systematic nature of these operations highlights the significant challenges Canadian authorities face in combating this escalating issue. Without comprehensive legal reforms and stricter enforcement measures, the country risks deeper entrenchment in this illicit cycle, leading to severe social repercussions.

1.4 Public Response

Faced with inadequate police responses, many vehicle owners have resorted to implementing their own anti-theft measures. Advanced security devices and traditional home-installed wheel locks are commonly used to deter theft. However, professional thieves often see these measures as minor obstacles, and even the most advanced systems have limitations. High installation costs and reduced effectiveness in extreme weather further compromise their reliability. Some owners attempt to safeguard their vehicles by parking in areas with a higher police presence or near police stations. Yet, such strategies offer no guarantee, as evidenced by reports of police chiefs' cars being stolen[6]. These incidents expose the boldness of car thieves and have sparked online criticism of law enforcement for failing to uphold basic security practices.

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[7]. The key components of the plan include:

- **Amendments to Criminal Laws**: Revising legislation to provide law enforcement and prosecutors with enhanced tools to tackle car 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 car 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 Role of Toronto

Toronto plays a central role in Canada's car theft crisis due to its large population, extensive vehicle ownership, and strategic location near major shipping ports. The city accounts for a significant percentage of national vehicle theft cases, driven by organized crime groups targeting both high-end and commonly used vehicles. Its proximity to international export routes facilitates the illegal shipping of stolen cars to overseas markets. Therefore, Toronto serves as an excellent case study for analyzing Canada's car theft situation.

1.7 Interim Result and Aim of the Paper

Several months have passed since the National Action Plan's implementation. Open Data Toronto has published theft-from-motor-vehicle data for Toronto reported from January 2014 to September 2024[8]. 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.

1.8 Estimand

The primary estimand of this study is the reduction in incidence 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 car 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[8]. 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 key fields described in Table 1:

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[9,10], and a collection of R packages were used in this study:

- tidyverse[11]
- here[12]
- lubridate[13]
- ggplot2[14]
- scales[15]
- knitr[16]
- kableExtra[17]
- topmodels[18]
- distributions3[19]
- MASS[20]
- sf[21]
- rstudioapi[22]
- opendatatoronto[23]
- janitor[24]

2.5 Data Management

Data cleaning steps are described in the Appendix. A sample set of the cleaned data of first few variables is presented in Table 2. 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

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

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 λ_i is the expectation of count of car theft occurrence, β_0 is the intercept, β_i is the corresponding coefficient for a predictor.

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 Section 4.

4 Results

4.1 Descriptives

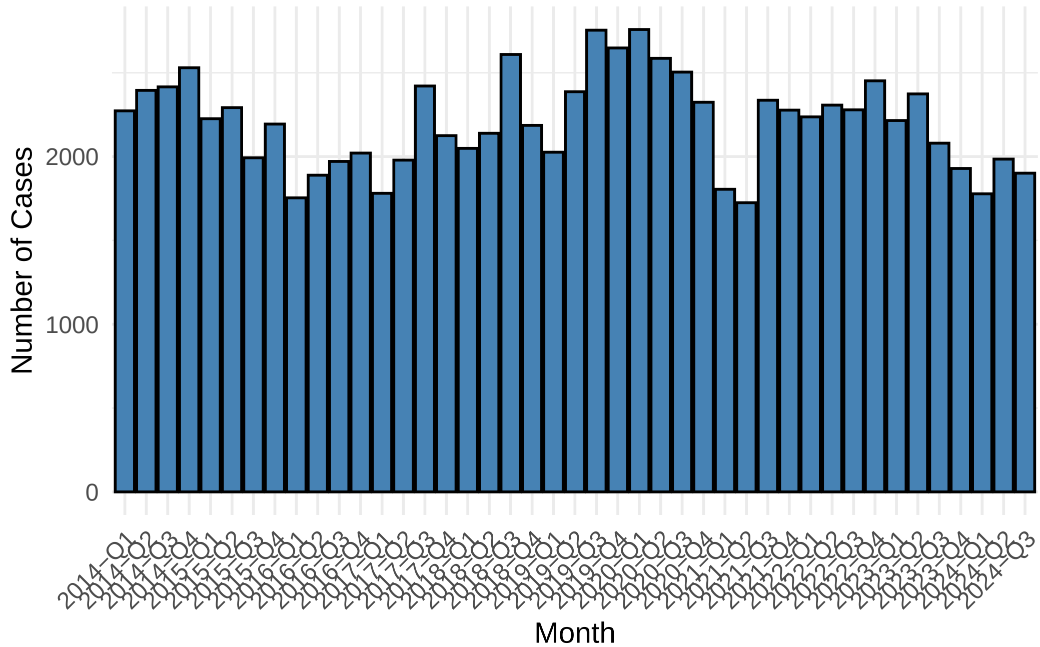

Figure 1: Histogram of quarterly count of car theft in Toronto

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.

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 D32 recorded the highest.

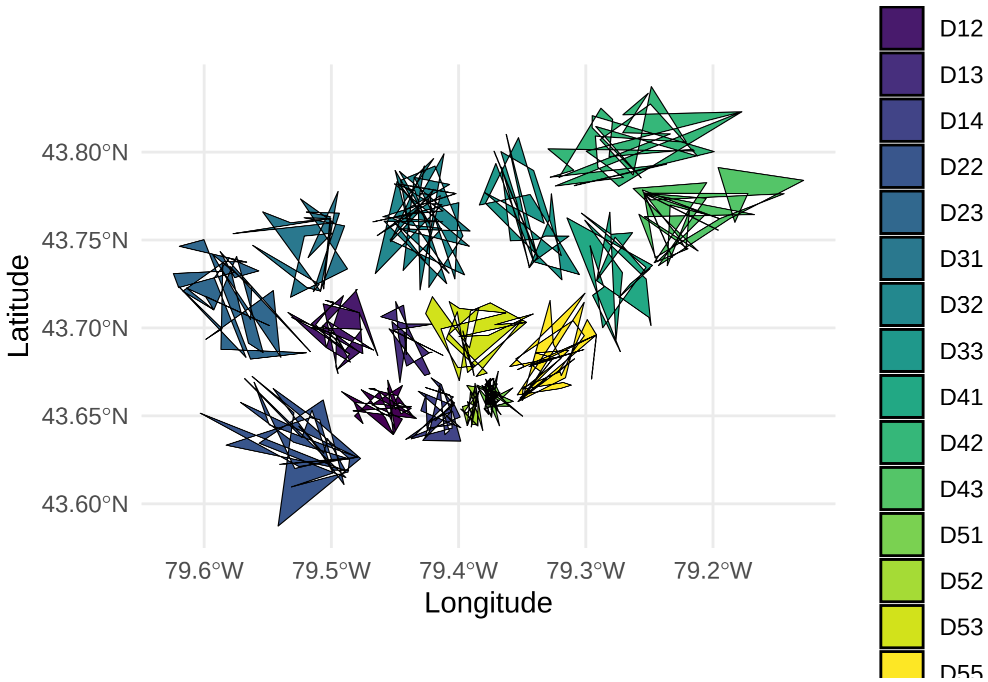

Figure 2: Spatial view of car theft cases by division for September 2024

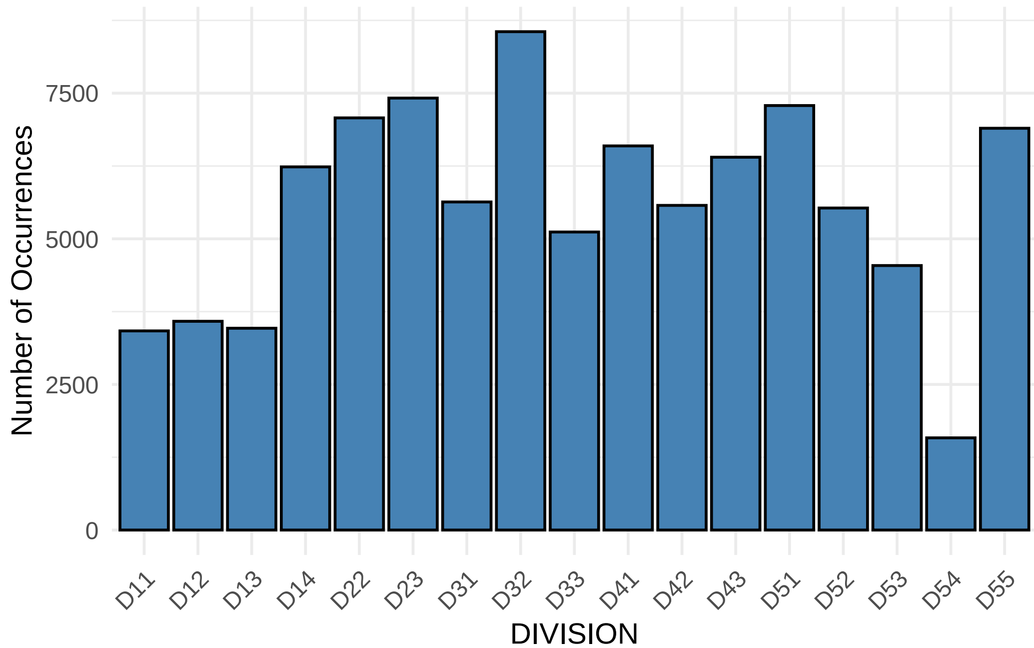

Figure 3: Barchart of count of occurrences by divisions

4.1.3 Premise Types

Figure 4 reveals that car theft cases occurred most frequently outside, followed by houses, 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.

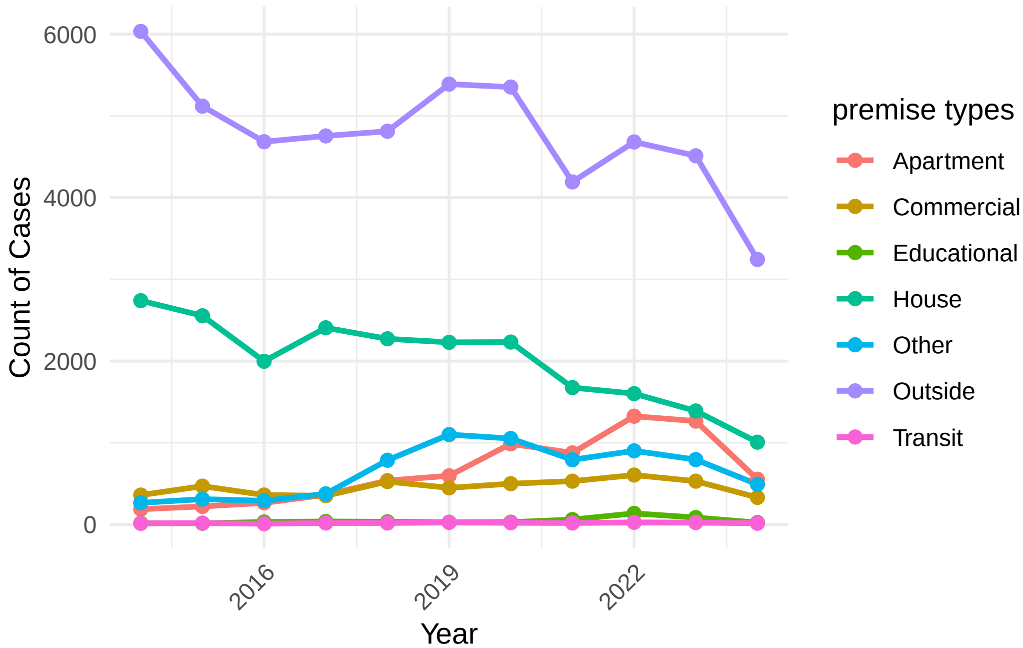

Figure 4: Linechart of count of occurrences by premise types and year

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 relatively stable over the years, while lighter cases experienced two increases in 2019 and 2022, with declines observed in 2016, 2021 and after 2024.

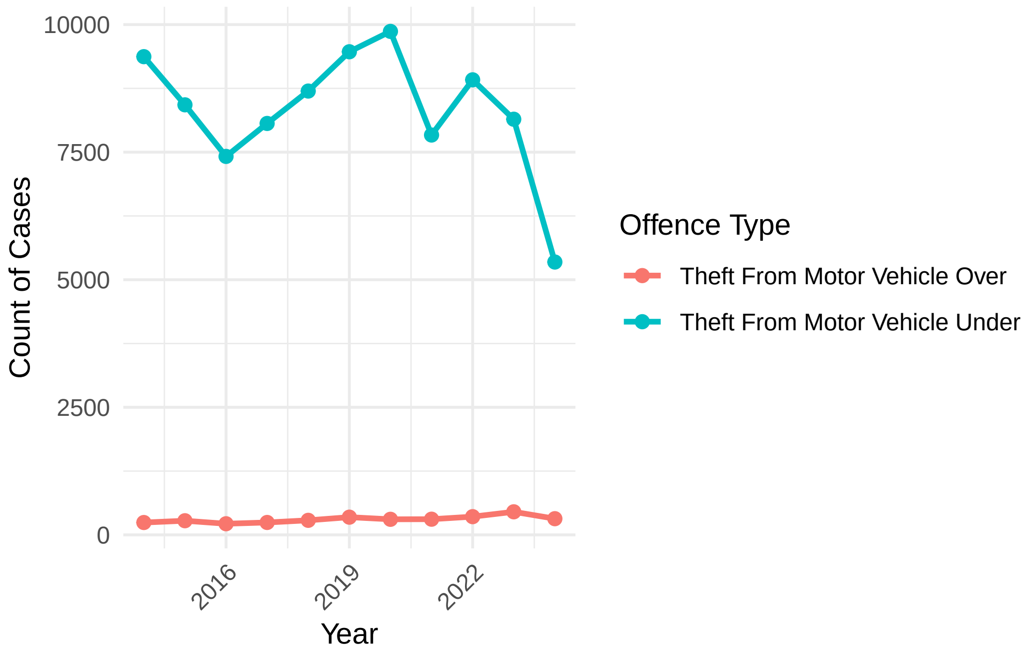

Figure 5: Linechart of count of occurrences by offence types and year

4.1.5 Day of the Week

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

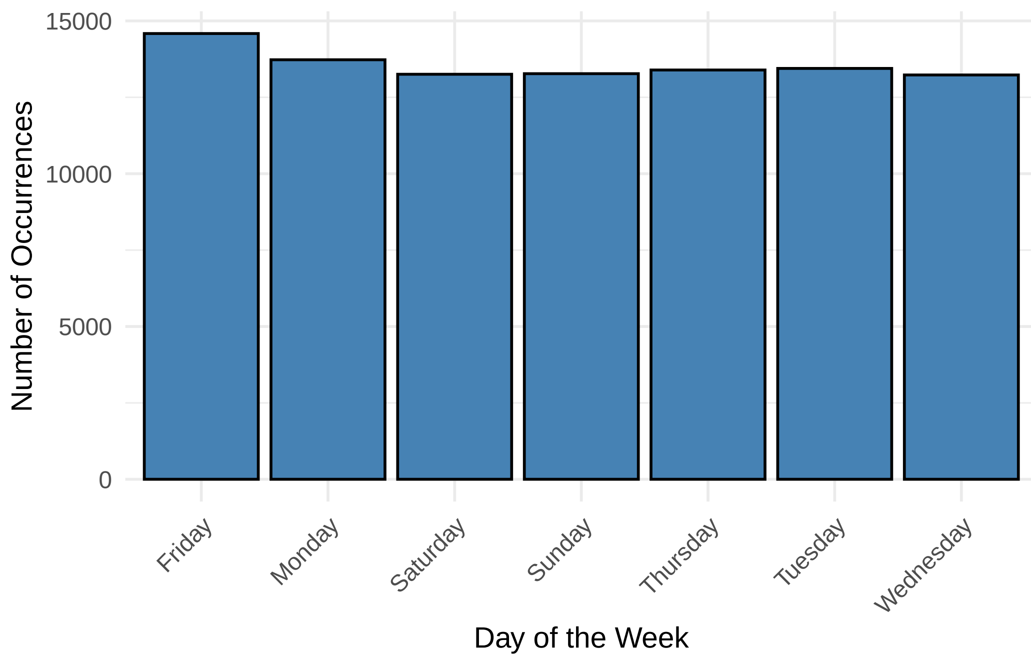

Figure 6: Barchart of count of occurrences by day of the week

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 big as 1,000 cases over a 10-year period, equivalent to approximately 30%.

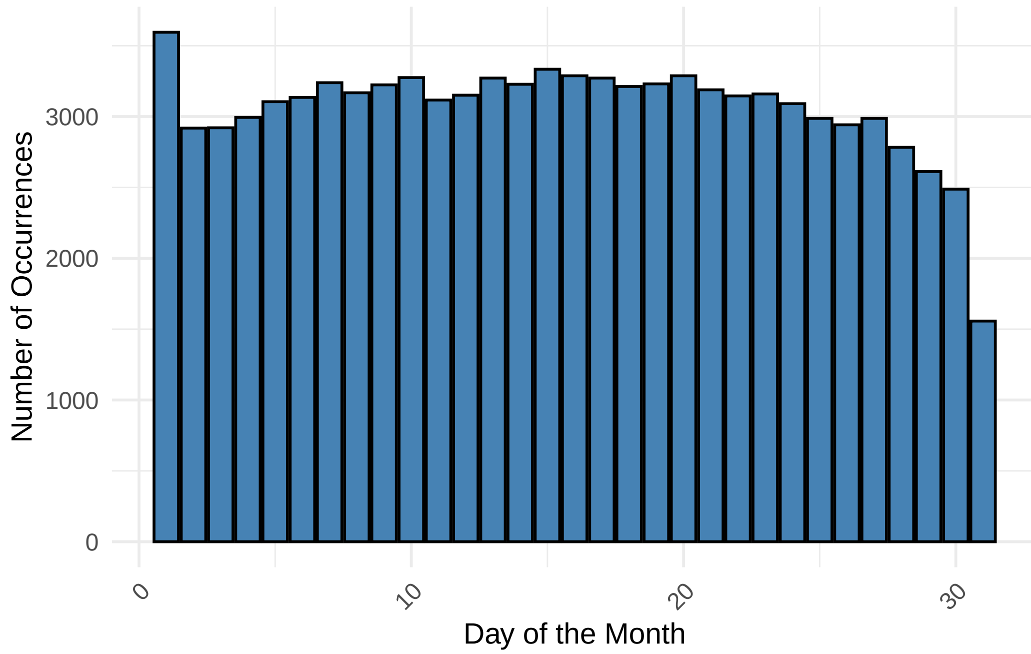

Figure 7: Barchart of count of occurrences by day of the month

4.2 Poisson Model

4.2.1 Point Estimates

Table 3 indicates that the variable “action”, indicator of implimentation of National Action Plan, 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

$$1 - exp(-0.1855) = 1 - 0.8307 = 16.93\%$$

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 3: Poisson regression results

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	6.4423	0.0569	113.2320	0.0000
time	0.0000	0.0000	2.9834	0.0029
action	-0.1855	0.0150	-12.3370	0.0000

Table 4: Poisson regression dispersion factor

Stats	Value
Dispersion Factor	14.7396

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.

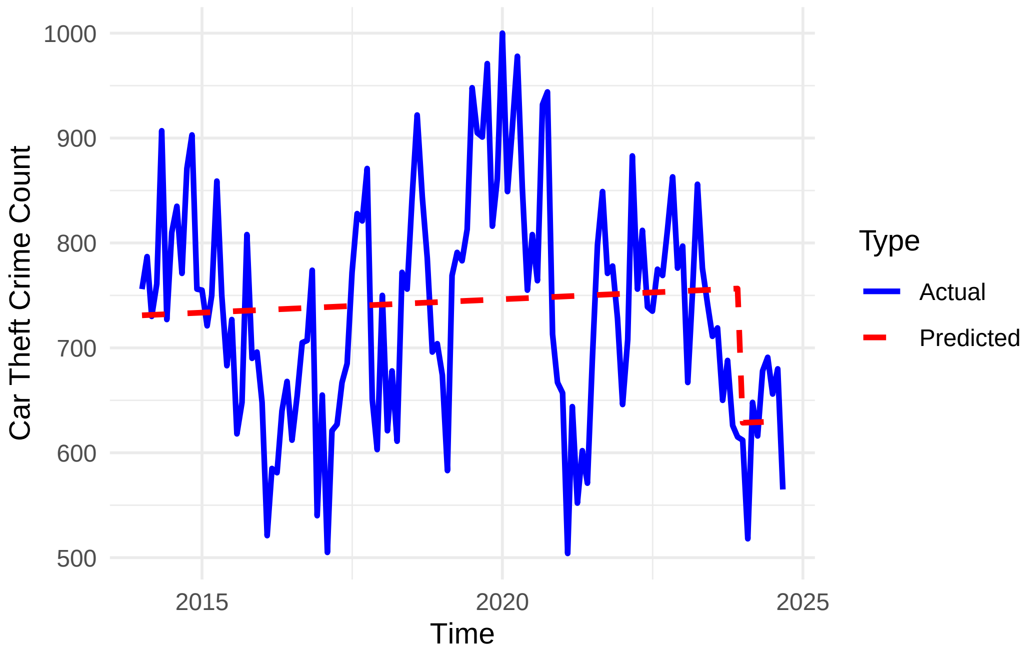

Figure 8: Poisson regression prediction

4.2.3 Model Diagnosis

The dispersion factor from Table 4 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 one influential point, corresponding to observation 122.

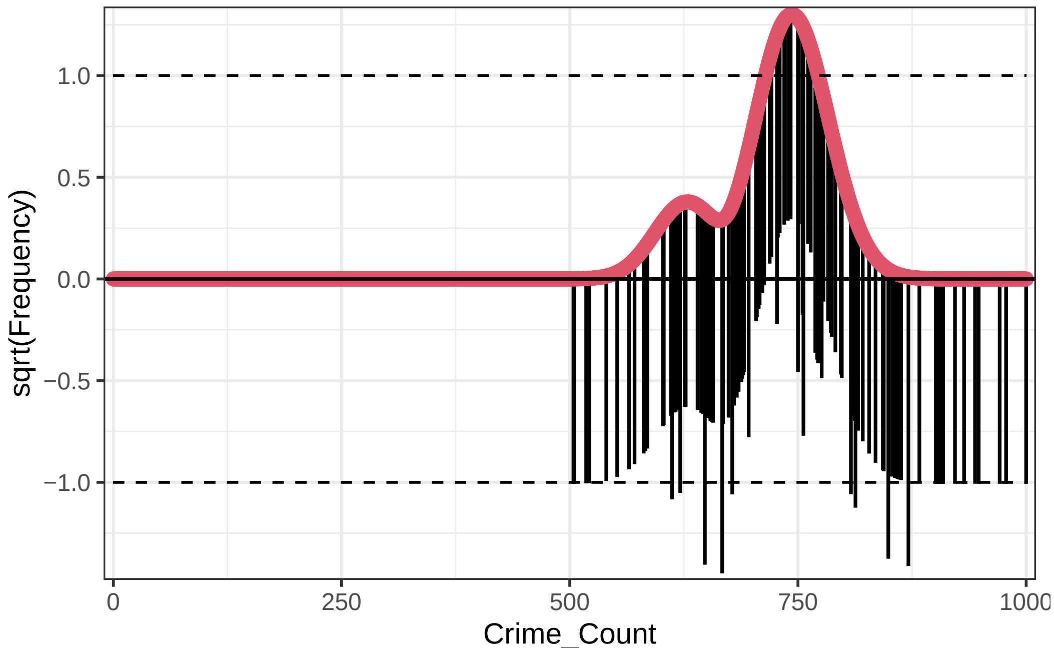

Figure 9: Poisson regression rootogram

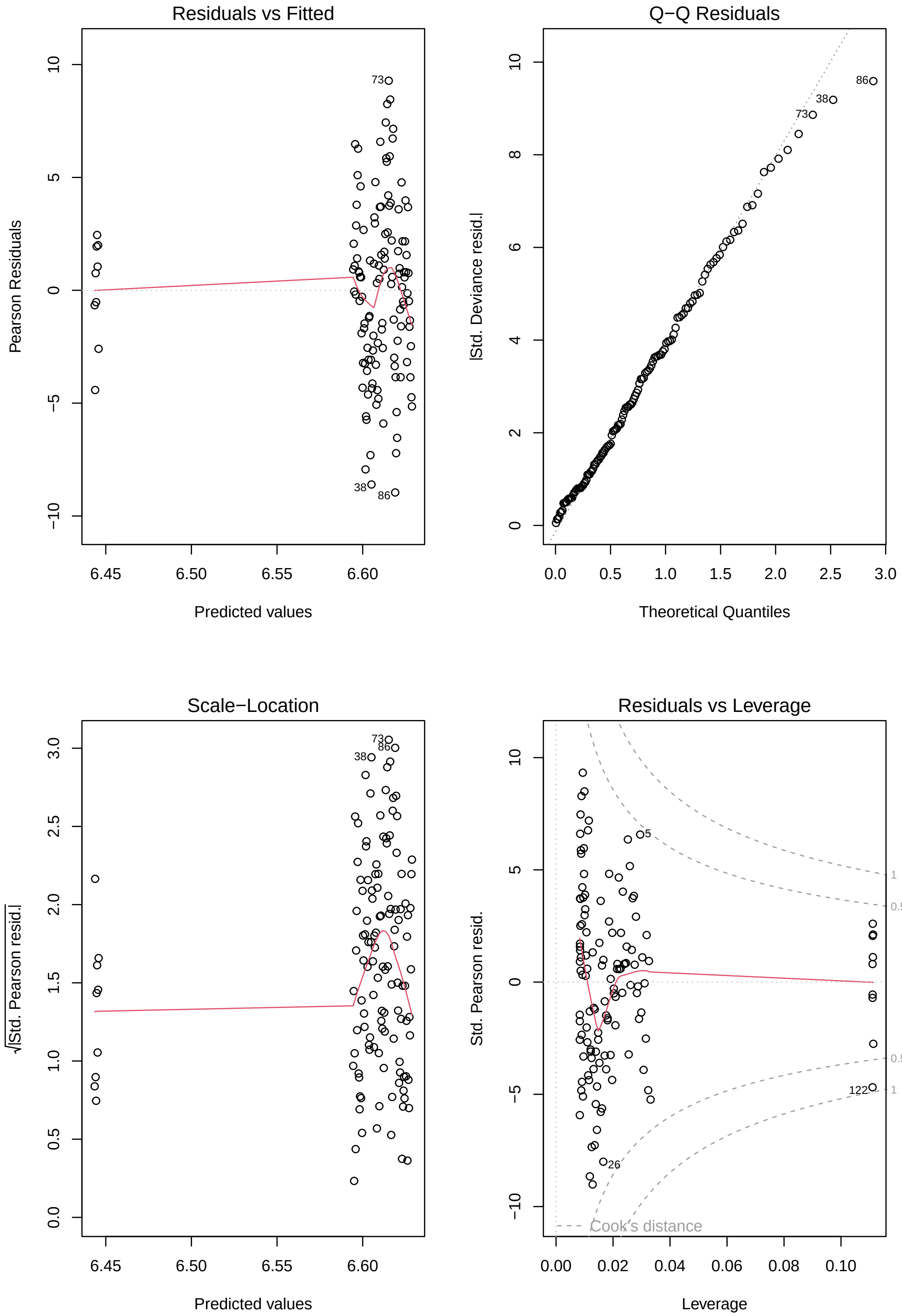

Figure 10: Poisson regression model diagnosis

4.3 Quasi-Poisson Model

Table 5 shows that the Quasi-Poisson model produced the same point estimate for the effect of “action”, indicating a 16.93% 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 6), which provides a more reliable and appropriate measure of precision.

Table 5: Quasi-likelihood Poisson regression results

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	6.4423	0.2184	29.4935	0.0000
time	0.0000	0.0000	0.7771	0.4386
action	-0.1855	0.0577	-3.2134	0.0017

Table 6: 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 7, Table 8, and Table 9 in Appendix 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 Summary of Findings

5.1.1 Impact of the National Action Plan

The implementation of the National Action Plan in early 2024 has led to a measurable reduction in car theft in Toronto. Our analysis indicates a 16.93% decline in the average monthly count of car theft cases after the plan's introduction, as shown by both Poisson and Quasi-Poisson regression models. Monthly crime counts fell by approximately 100 cases per month following the policy's enactment. Compared with the Poisson regression model, the Quasi-Poisson model produced the same point estimate but provided a more precise confidence interval by addressing overdispersion. These findings underscore the potential of government-led initiatives in reducing auto theft, though long-term monitoring is needed to evaluate sustained effects.

5.1.2 Spatial and Temporal Patterns of Car Theft

Spatial analysis revealed notable differences in car theft rates across Toronto's police divisions. Division 32 consistently experienced the highest theft rates due to its urban environment, heavy traffic, and role as a commercial hub, making it an attractive target for criminals. In contrast, Division 54 reported the lowest theft rates, likely due to its suburban setting, lower population density, and reduced vehicular activity, enabling more effective policing. Outdoor parking areas had the highest theft frequencies, reflecting elevated risks for vehicles parked outside. Temporally, thefts peaked in 2019 and 2022-2023, with a decline after 2024. A temporary reduction in early 2021 was likely caused by decreased mobility and public activity due to the COVID-19 pandemic. Notably, car thefts were most frequent at the beginning of the month and dropped significantly toward the month's end, warranting further investigation into this pattern.

5.1.3 Effectiveness of the National Action Plan

Although the National Action Plan appears to have reduced overall car theft cases, its effectiveness likely varies by division and offense type. The higher occurrence of "Theft From Motor Vehicle Under" cases may be linked to less expensive vehicles with weaker anti-theft features, making them more susceptible to theft. Similarly, thefts involving residential properties and outdoor parking areas underscore the need for targeted security enhancements in these settings. These findings highlight the importance of tailoring crime prevention strategies to address distinct regional challenges.

5.2 Weaknesses and Limitations

This study has several limitations. First, the analysis relied on reported cases, potentially underestimating the true extent of car theft due to unreported incidents. Second, the overdispersion identified in the Poisson model indicates variability that may not have been fully captured by the included predictors. While the Quasi-Poisson model improved standard error estimates, incorporating additional covariates such as socioeconomic factors or policing intensity could enhance model accuracy. Interaction effects were not examined in this study. Lastly, the relatively short timeframe since the National Action Plan's implementation limits the ability to assess its long-term effects.

5.3 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.

A Appendix

A.1 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.

Details are described in a script.

A.2 Additional Tables

Table 7: 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
action	-0.1859329	0.0480472	-3.8697965	0.0001173

Table 8: 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 9: 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

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