# Temporal and Spatial Analysis of Hate Crimes in Toronto\*

Uncovering Neighborhood Disparities and Bias Trends Across the City

# Tommy Fu

September 24, 2024

This paper analyzes the temporal and spatial patterns of hate crimes in Toronto focusing on trends over time and neighborhood disparities. Toronto Open Datahate crime is used to explore variations in crime frequency and the prevalence of biases such as race, religion and sexual orientation. The results highlight distinct increasing trends and reveal youge-bay corridor neighborhoods with highest concentrations of bias-motivated incidents; these findings offer insights for addressing hate crimes and police enforcement in the city.

## Table of contents

1	Introduction	
2	Data	
	2.1 Measurement and packages	
	2.2 Data cleaning	
	2.3 Observation of cleaned data	
	2.4 Basic Summary Statistics of the Data	
3	Results	
	3.1 Number of Hate Crimes Across Time	
	3.2 Analysis of Hate Crimes by Bias Type	
	3.3 Racial Bias Breakdown by Neighborhood	
4	Discussion	
	4.1 First discussion point	

<sup>\*</sup>Code and data are available at: https://github.com/YichengFu/hate\_crimes.git

References			
4.4	Weaknesses and next steps	7	
4.3	Third discussion point	7	
4.2	Second discussion point	1	

#### 1 Introduction

Hate crimes are a significant incident reflecting deep-rooted prejudice and discrimination within communities. Hate-crime victimization against racially visible people is of growing concern (Chongatera 2013). These crimes not only impact individuals but also harm the society often leaving individuals feeling unsafe. Social violence omit both the daily violence suffered by certain social categories and its many impacts on the victims (Dalphond 2021). In Toronto, understanding the patterns and dynamics of hate crimes is crucial for addressing their causes and mitigating their effects. While racial and cultural diversity initiatives are central in hate crime policy, combating racially motivated hate crime is often obscured by matters considered more significant by police (Bryan 2019). This paper aims to fill that gap by providing an in-depth analysis of hate crimes in Toronto over time and across different neighborhoods.

This study focuses exploring two primary questions: how hate crimes in Toronto have evolved over time and whether certain neighborhoods experience a disproportionate concentration of bias-motivated incidents. Using Toronto open Data hate crime from 2018 to 2023 I analyzes temporal trends to identify peaks and patterns in the frequency of reported incidents. Additionally, the research examines whether specific biases (such as race, religion, or sexual orientation) are more prevalent in particular areas contributing to an understanding of neighborhood-level disparities. The results provide insight into both the temporal and spatial aspects of hate crimes, shedding light on how bias manifests in different contexts within the city.

The data section will introduced the detail of the data set used in this research in Section 2 – Data. The variables as well as the cleaning process will be discussed in this section. Section 3 will focus on the findings and the visualization of the analysis. Section 4 talks about the limitation of this research and potential error caused by research design or the natural form of data. lastly, the conclusion part raps up the discovers and summarizes all the findings into a short paragraph.

#### 2 Data

## 2.1 Measurement and packages

The Data set used in the analysis is gathered from Open Data Toronto through the Open Data Toronto (Gelfand 2022) and used the statistical software R (R Core Team 2023) for importing data, data cleaning and testing data. The data source "Crime Data" is collected from Toronto Police starting from 2018 to the end of 2023. It includes both temporal and spatial attributes. Other packages were used for analyzing the data such as ggplot (Wickham 2016), knitr(Xie 2023), tidyverse (Wickham et al. 2019), lubridate (Grolemund and Wickham 2011), tinytex(Xie 2024), dplyr (Wickham et al. 2023).

Data contains around 1400 observations and contains the occurrence date and specific time where the incident happened and the date reported to the police. The reason for committing hate crime is categorized as race bias, religion bias and sexual orientation bias etc. The motive for committing a crime the illegal activity and the neighborhood where the crime occurred are documented by the police throughout the years. Furthermore, the type of location such as park, apartment and school are documented to form the detailed data set and is named "Hate Crime".

## 2.2 Data cleaning

After observing the data, some observations were dropped due to missing values in location type meaning the recorder had a hard time describing the location characteristics. Therefore, these observations were dropped out of the cleaned data set and will not be included in further data analysis. Date is critical in our data investigation, observations where the reported time is before occurrence time is dropped to assure data validity. Since the data set is from Open Data Toronto the quality of the data is decent. Further cleaning process is unnecessary due to origin high quality of data set.

## 2.3 Observation of cleaned data

A sample of observation of cleaned data is displayed in Table 1. This table includes key variables of interest that will be used for further analysis. Specifically, it contains the bias type, which indicates whether the crime was motivated by factors such as race, religion, or sexual orientation. The date of the incident is provided, allowing for temporal analysis of hate crime trends over time. Additionally, the neighborhood where each crime occurred is included, which is crucial for understanding geographic characteristics and identifying potential hotspots for hate crimes within Toronto. The offense type records the legal classification of the crime, such as assault or mischief providing insight into the nature of the incidents. Lastly, the arrest

status variable indicates whether law enforcement made an arrest in response to the reported crime, which is an important indicator of justice system responses to hate crimes.

Table 1: Sample of Cleaned Data with Selected Variables

Year	RaceBias	Sex.	RLGBias	Location	Offense	Arrest
2021	none	none	jewish	Etobicoke City Centre	Mischief Under \$5000	NO
				(159)		
2018	none	none	$\operatorname{muslim}$	Bay-Cloverhill (169)	Assault	NO
2018	none	none	$\operatorname{muslim}$	Oakdale-Beverley	Assault	YES
				Heights (154)		
2020	none	none	$\operatorname{muslim}$	Cliffcrest (123)	Assault	NO
2019	none	none	$\operatorname{muslim}$	Fort York-Liberty	Criminal Harassment	NO
				Village (163)		
2019	none	none	jewish	Bathurst Manor (34)	Uttering Threats -	YES
				, ,	Bodily Harm	
2020	black	none	none	Yonge-St.Clair (97)	Assault	NO
2020	black	none	none	O'Connor-Parkview (54)	Mischief Under \$5000	NO

Sample data visualization of what the data looks like containing the variable of intersts. Note the column sex. stands for sexual orientation. RLGbias stands for religion bias.

# 2.4 Basic Summary Statistics of the Data

A general summary statistic is shown Table 2. Since hate crimes are relatively rare events, the data may show an uneven distribution across different years and neighborhoods. Some years may exhibit higher counts due to specific incidents or socio-political factors that led to spikes in reporting, while other years may show fewer cases, resulting in an unbalanced distribution. Due to the categorical nature of many key variables, such as bias types (race, religion, sexual orientation), and the relatively small number of observations per category, more advanced summary statistics (e.g., mean, standard deviation) are not as meaningful in this context. Instead, the focus is on counting occurrences and understanding the distribution of incidents across time and location. Therefore, we limit the analysis to counts and proportions rather than providing more traditional numeric summary statistics. Further analysis of location and its relationship to number of hate crimes will be shown in Section 3.

Table 2: Number of Observations by Year

OCCURRENCE_YEAR	Observation_Count
2018	129
2019	128

Table 2: Number of Observations by Year

OCCURRENCE_YEAR	Observation_Count
2020	210
2021	254
2022	235
2023	357

# 3 Results

A sample observation is shown in Table 3. This table indicates neighborhoods in Toronto with more than 20 Hate Crimes from 2018 to 2023. The number of 20 hate crimes is manually selected by the author after inspecting the data to avoid overlapping of the visualization of the table or cluster of data. Only the significant neighbourhoods are selected to include in this table to give a brief observation of the number of crime case numbers in different area in Toronto.

Table 3: Neighborhoods with more than 20 Hate Crimes from 2018 to 2023

NEIGHBOURHOOD_158	Crime_Count
Yonge-Bay Corridor (170)	49
Church-Wellesley (167)	46
York University Heights (27)	39
Annex (95)	38
Downtown Yonge East (168)	37
Moss Park (73)	32
NSA	28
Kensington-Chinatown (78)	25
Wellington Place (164)	25
Oakdale-Beverley Heights (154)	23
Newtonbrook West (36)	21
St Lawrence-East Bayfront-The Islands (166)	21
University (79)	21

## 3.1 Number of Hate Crimes Across Time.

The time series graph regarding number of hate crimes is shown Figure 1. While the data reveals short-term variability with notable spikes and drops over several months the overall trend suggests an upward trend in hate crime incidents from 2018 to 2023. Specifically, there

are sharp increases in hate crime counts around late 2020 and mid-2022 followed by periods of relative decline. This phenomenom of huge spikes could be due to world-wise disease COVID-19 but further justification is needed. Despite these fluctuations the general pattern indicates that hate crimes have become more frequent in recent years.

The x-axis is divided into three-month intervals to avoid the overcrowding of data points and overlapping labels ensuring that the time progression remains readable. The consistent increase in hate crimes despite periodic dips highlights the need for a deeper exploration of factors that may have contributed to this rise.

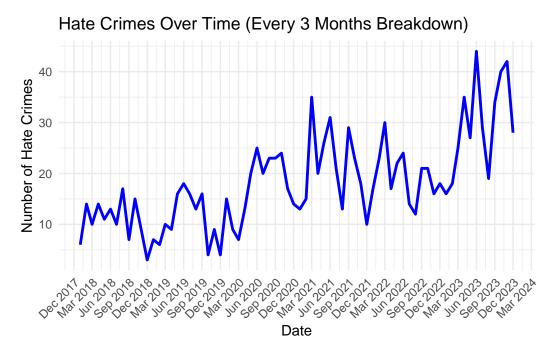


Figure 1: Time Series Plot for Hate Crimes Count

# 3.2 Analysis of Hate Crimes by Bias Type

According to (fig2?), it illustrates the count of hate crimes by bias type from 2018 to 2023 broken down into half-year intervals. Hate crimes involving race bias (in red) consistently form the largest proportion of incidents across all half-year periods with a marked increase especially in the later periods (2022 and 2023). Religion bias (in green) remains a significant contributor to hate crimes, steadily increasing over time, particularly during 2022 and 2023. Sexual orientation bias (in blue) while present constitutes a smaller proportion of the total hate crimes though it shows a noticeable rise in recent years.

The general trend indicates an upward trajectory in the total number of hate crimes across all bias types with a sharp increase in the later half-year periods of 2022 and 2023. This

suggests that hate crimes have become more frequent and more diverse in bias type over time highlighting the need for continued focus on these issues.

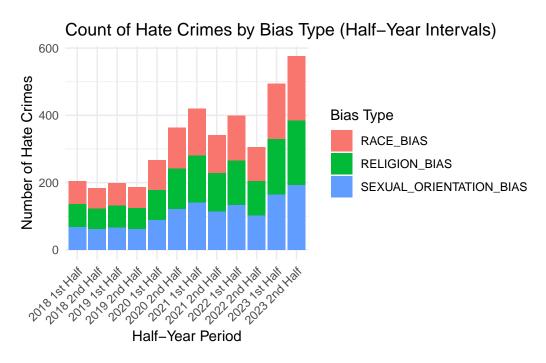


Figure 2: The Count of Hate Crimes by Bias Types

#### 3.3 Racial Bias Breakdown by Neighborhood

As previously mentioned in Table 3, the Yonge-Bay Corridor records the highest number of hate crimes overall. In this section, the analysis delves deeper into the racial biases driving these crimes. Table Table 4 provides a detailed breakdown revealing that hate crimes specifically targeting Black individuals are most prevalent in the Yonge-Bay Corridor, Moss Park and York University Heights. This neighborhood not only has the highest overall incidence of hate crimes but also stands out as the primary location for racially motivated offenses against Black individuals. These findings emphasize the significance of addressing racial bias in areas with concentrated hate crime activity, particularly in the Yonge-Bay Corridor. Furthermore, Table 4 and Table 3 provides insights for black individuals to choose their neighborhood to live in.

Table 4: Number of Hate Crimes Targeting Black Individuals by Neighborhood

NEIGHBOURHOOD_158	Crime_Count
Moss Park (73)	10

Table 4: Number of Hate Crimes Targeting Black Individuals by Neighborhood

NEIGHBOURHOOD_158	Crime_Count
Yonge-Bay Corridor (170)	10
York University Heights (27)	10
NSA	9
North St.James Town (74)	8
Church-Wellesley (167)	7
Downtown Yonge East (168)	7
High Park North (88)	6
New Toronto (18)	6
Clairlea-Birchmount (120)	5

The bar chart in Figure 3 illustrates the distribution of hate crimes motivated by racial bias from 2018 to 2023. The data clearly shows that hate crimes targeting Black individuals make up the majority of incidents across all years with a particularly sharp increase in 2020, which remains high in the subsequent years. Although hate crimes against other racial groups—such as White, South Asian and Indigenous individuals—are present they constitute a much smaller portion of the total. The chart highlights the consistent and disproportionate targeting of Black individuals especially during the observed rise in hate crimes starting in 2020.

## 4 Discussion

#### 4.1 First discussion point

#### 4.2 Second discussion point

### 4.3 Third discussion point

### 4.4 Weaknesses and next steps

Weaknesses and next steps should also be included.

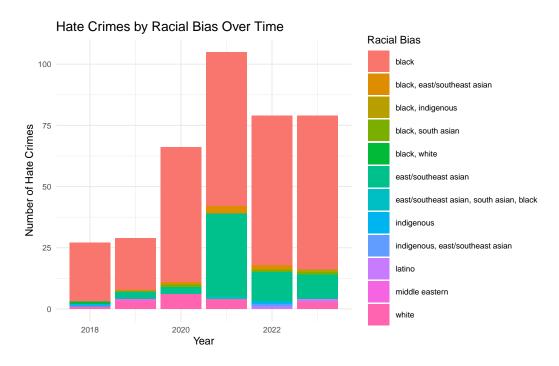


Figure 3: Hate Crimes by Racial Bias Over Time

## References

Gelfand, Sharla. 2022. Opendatatoronto: Access the City of Toronto Open Data Portal. https://CRAN.R-project.org/package=opendatatoronto.

Grolemund, Garrett, and Hadley Wickham. 2011. "Dates and Times Made Easy with lubridate." *Journal of Statistical Software* 40 (3): 1–25. https://www.jstatsoft.org/v40/i03/.

R Core Team. 2023. R: A Language and Environment for Statistical Computing. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Wickham, Hadley. 2016. *Ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York. https://ggplot2.tidyverse.org.

Wickham, Hadley, Mara Averick, Jennifer Bryan, Winston Chang, Lucy D'Agostino McGowan, Romain François, Garrett Grolemund, et al. 2019. "Welcome to the tidyverse." *Journal of Open Source Software* 4 (43): 1686. https://doi.org/10.21105/joss.01686.

Wickham, Hadley, Romain François, Lionel Henry, Kirill Müller, and Davis Vaughan. 2023.

\*Dplyr: A Grammar of Data Manipulation. https://CRAN.R-project.org/package=dplyr.

\*Via Vibri 2022 Variety A Consent Paymens Paglages for Daymenia Report Consention in a

Xie, Yihui. 2023. Knitr: A General-Purpose Package for Dynamic Report Generation in r. https://yihui.org/knitr/.

——. 2024. Tinytex: Helper Functions to Install and Maintain TeX Live, and Compile LaTeX Documents. https://github.com/rstudio/tinytex.