

Temporal and Spatial Analysis of Hate Crimes in Toronto*

Uncovering Neighborhood Disparities and Bias Trends Across the City

Tommy Fu

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This paper analyzes the temporal and spatial patterns of hate crimes in Toronto focusing on trends over time and neighborhood disparities. Toronto Open Data-hate 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.

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*Code and data are available at: https://github.com/YichengFu/hate_crimes.git

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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 (Mercier-Dalphon and Helly 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 Used

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
2023	black	none	none	Wexford/Maryvale (119)	Mischief Under \$5000	NO
2022	none	2slgbtq+	none	Banbury-Don Mills (42)	Mischief Under \$5000	NO
2021	black	none	none	Humber Heights-Westmount (8)	Uttering Threats - Bodily Harm	NO
2023	none	2slgbtq+	none	Rosedale-Moore Park (98)	Mischief Under \$5000	NO
2022	none	2slgbtq+	none	Church-Wellesley (167)	Mischief Under \$5000	NO
2019	none	none	jewish	Church-Wellesley (167)	Mischief Under \$5000	NO
2022	none	none	none	Victoria Village (43)	Uttering Threats - Bodily Harm	NO
2018	none	none	none	Junction Area (90)	Assault	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. After inspecting the data age and language biases are dropped due to small sample size which indicates these two biases are less likely to be taken place in Toronto Area. Some years may exhibit higher counts due to specific incidents or 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
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 phenomenon of huge spikes could be due to world-wide 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.

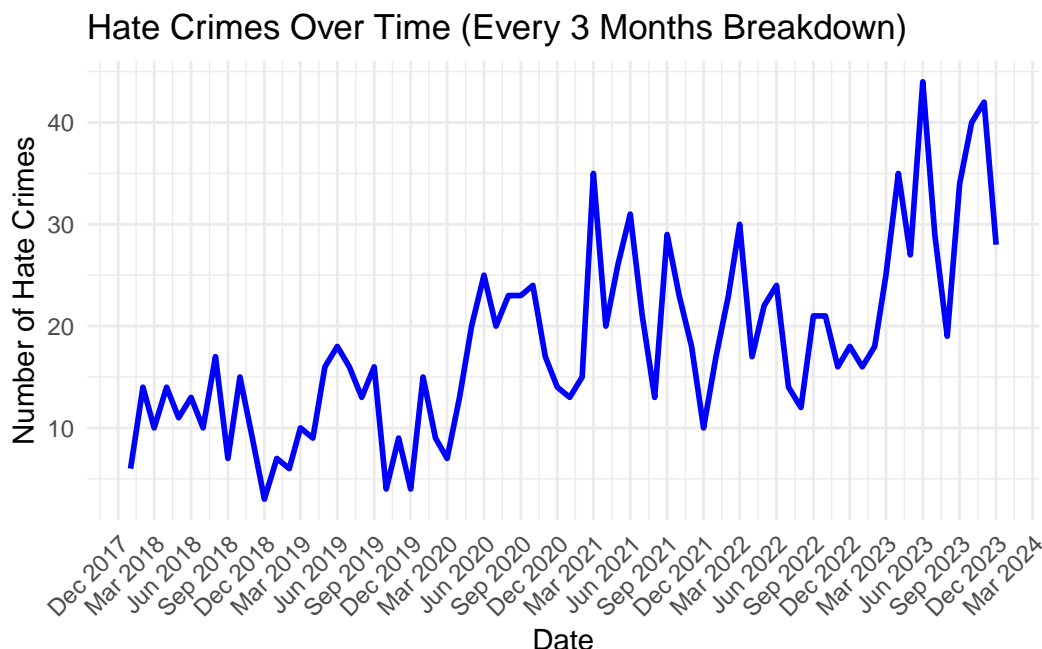


Figure 1: Time Series Plot for Hate Crimes Count

3.2 Analysis of Hate Crimes by Bias Type

According to Figure 2, 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.

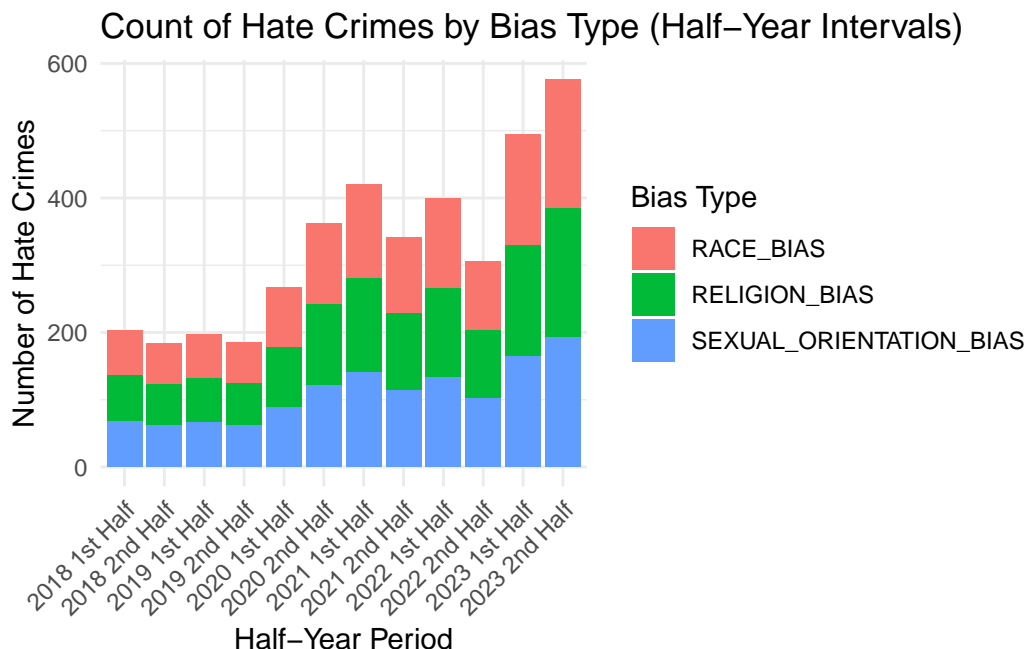


Figure 2: The Count of Hate Crimes by Bias Types

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 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
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.

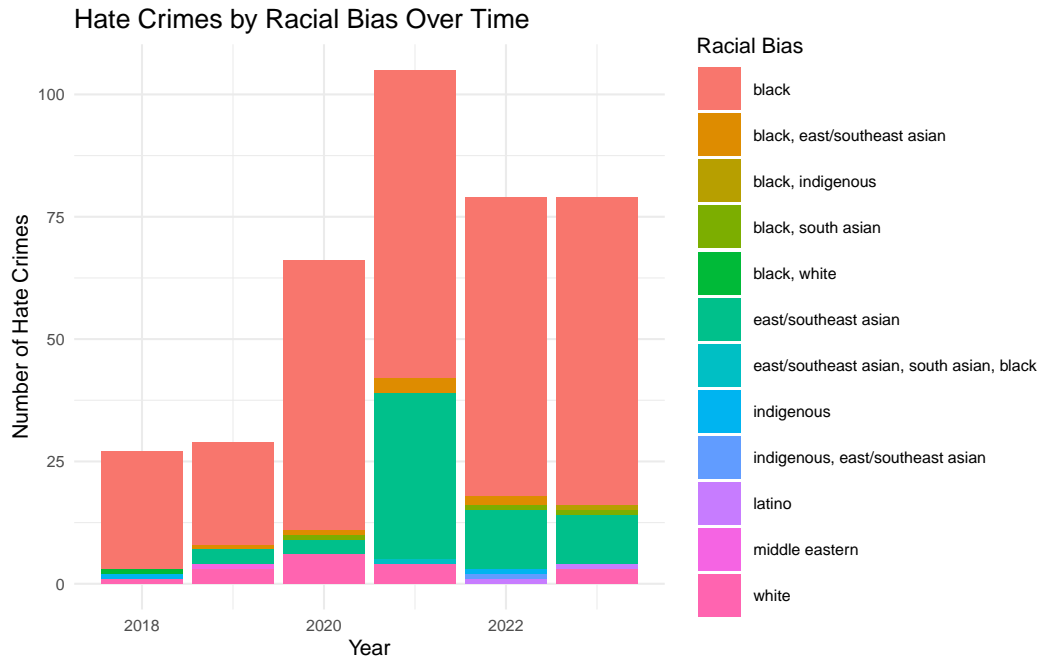


Figure 3: Hate Crimes by Racial Bias Over Time

4 Discussion

4.1 Rising Trend of Hate Crimes

The time-series analysis in Figure 1 reveals a steady increase in hate crimes in Toronto from 2018 to 2023 with spikes in 2020 and 2022. These years coincide with significant societal disruptions caused by the COVID-19 pandemic which drastically altered daily life, the economy and social dynamics worldwide. The pandemic not only led to a global health crisis but also intensified economic disparities, social isolation, and general uncertainty.

The pandemic's economic impacts including layoffs from work and rising inflation intensified societal stresses. In Table 2 the basic summary statistics shows how hate crimes dramatically increase in 2020 which coincides with the time series graph in Figure 1 and the discussion in COVID-19 impacts. As many people faced severe financial problem and emotional strain marginalized communities often became scapegoats for these frustrations. In particular, black race communities worldwide experienced increased hate crimes. Further analysis on hate crimes towards black race is included in [Disproportionate Racial Bias](#). This spike in hate crimes during 2020 and 2022 aligns with a broader pattern of rising xenophobia and racial targeting exacerbated by misinformation and heightened racial tensions. The pandemic appears to have not only exposed underlying societal inequalities but also amplified them.

Moreover, the upward trajectory of hate crimes during these years suggests that existing hate crime prevention policies may have been insufficient in addressing the root causes of such bias-motivated offenses. The stress brought by COVID-19 acted as a trigger for already existing tensions which implies that long-standing systemic issues regarding racial discrimination were not adequately addressed.

4.2 Disproportionate Racial Bias

According to Figure 3, the discrimination towards black race individuals has a significantly lead comparing to hate crimes towards other races. The data consistently show that hate crimes motivated by racial bias particularly those targeting Black individuals form the largest portion of the incidents across all years. This finding aligns with global concerns over racial discrimination and reinforces the idea that racial bias remains a significant driver of hate crimes in Toronto. Specific neighborhoods, such as Yonge-Bay Corridor and York University Heights show a high concentration of such incidents emphasizing the need for localized responses. These neighborhoods may require targeted community outreach and police presence to address racial tensions and foster exclusivity. The dominant status of racial bias in hate crimes suggests that efforts to combat racism must remain a central focus of anti-hate crime policies.

4.3 Spatial Variances and Neighborhood Hotspots

The spatial analysis underscores that hate crimes are not evenly distributed across Toronto, with certain neighborhoods experiencing disproportionately higher rates of incidents shown in Table 3. For instance, the Yonge-Bay Corridor and Church-Wellesley neighborhoods consistently rank among the highest in hate crime occurrences. This geographic concentration suggests that specific local tensions may contribute to the higher rates of hate crimes in these areas. Furthermore in Table 4, the Yonge-Bay Corridor and Church-Wellesley neighborhoods continue to be prominent hotspots for hate crimes targeting Black individuals. This trend emphasizes the persistent racial bias and discrimination in these parts of the city reflecting broader societal challenges that Black communities face. These areas have seen a disproportionately high number of incidents compared to other neighborhoods in Toronto. Understanding the root causes of these differences whether they stem from economic inequality, social marginalization or historical prejudices can guide more effective policy interventions. Targeted strategies that address the unique conditions of these neighborhoods are crucial in reducing the incidence of hate crimes and fostering safer and more inclusive communities.

4.4 Weaknesses and next steps

The analysis of hate crimes in Toronto reveals several important findings but there are also notable limitations that must be addressed. First, the data used is limited to reported incidents which may not capture the full scope of hate crimes occurring in the city as many

incidents go unreported due to fear distrust of authorities, or other reasons. Additionally, the analysis relies heavily on the available police data which may have biases in how crimes are classified or reported. One significant limitation of the data structure is that it heavily relies on categorical variables such as race bias, religion bias, and sexual orientation bias without providing in-depth contextual information about each incident. This structure limits the ability to explore nuances within hate crimes such as intersecting identities (e.g., race and religion) or the background of the victims. Furthermore, the data does not account for the severity or outcome of each incident which could offer insight into the effectiveness of law enforcement responses. Another limitation is the time-frame of the data which still miss long-term trends or cyclical patterns in hate crimes. These limitations suggest that future research should aim to incorporate community surveys or qualitative studies to capture a broader perspective of hate crime experiences. Moving forward, a deeper exploration of the factors driving the concentration of hate crimes in specific neighborhoods and the effectiveness of existing interventions is crucial.

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