Have Toronto Police Services been successful in materially reducing the frequency of major crimes in high-risk Toronto neighbourhoods over the past 10 years?*

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The data set **Major Crime Indicators** from City of Toronto's Open Data Portal was analyzed to uncover the Toronto Police Service's material success in reducing the frequency of major crimes in high-risk Toronto neighbourhoods over the 10 year period from 2014 to 2023, inclusive. This analysis reveals that for neighbourhoods in which their major crime rates are already the highest, there is little progression over the years in those neighbourhoods' crime rates dropping comparatively to other neighbourhoods. This lack of progression confirms the Toronto Police Service has not materially reduced the frequency of major crimes in high-risk neighbourhoods in this 10 year period. To frame potential causes, the Toronto Police Service's Operating Impact is analyzed and the complex interactions between socio-economic factors, policing, and major crime rates are considered.

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*Code and data are available at: https://github.com/brooklinbecker/major_crimes.git

1 Introduction

Prior to 2015, the city of Toronto had been experiencing a continuation of a downward trend in the police-reported crime rate that had begun in the early 1990s, marked by the 'crime drop' of that same decade (Farrell, Hodgkinson, and Andresen 2018). In fact, the "police-reported crime rate in 2014 was the lowest rate recorded since 1969" (Farrell, Hodgkinson, and Andresen 2018), especially in terms of severity and sheer volume (Boyce 2015). However, 2015 marked a turning point wherein the police-reported crime rate *increased* by 3% from 2014 (Allen 2016). Though still measuring at 29% lower than the decade previous, the 10 year period between 2014 to 2023, inclusive, has since continued to see a significant change in socio-economic conditions for Toronto's population, the effects of which are deeply intertwined with crime frequency.

To analyze Toronto Police Services' response to these dynamic conditions, I utilized the **Major Crime Indicators data set** from **City of Toronto's Open Data Portal** to compare frequency and distribution of major crime indicators in high-risk[1] neighbourhoods year-over-year from 2014 to 2023, inclusive (Gelfand 2022). When conducting the analysis of the major crime frequencies, I analyzed both absolute and relative results to better identify patterns and variance amongst the data, as evident in Section 2.1 Table 1 and Table 2. Within this analysis, I aimed to satisfy the question: have Toronto Police Services been successful in materially reducing the frequency of major crimes in high-risk Toronto neighbourhoods over the past 10 years?

The 158 Neighbourhood configuration (new geographical boundaries implemented circa 2022 (Administration 2022)) was chosen as opposed to taking data from the previous 140 Neighbourhood configuration to reflect the current City of Toronto neighbourhood composition. Figure 1 provides a visual representation of the 10 most high-risk neighbourhoods, where 1 = West Humber-Claireville; 2 = York University Heights; 3 = Annex; 4 = Kensington-Chinatown; 5 = Wellington Place; 6 = Yonge-Bay Corridor; 7 = Downtown Yonge East ; 8 = Moss Park; 9 = West Hill. 'NSA' is listed within the top 10 high-risk neigbourhoods, however it is not defined on Open Data Toronto, the Toronto Police Service's website, nor any other resource I can identify. As it cannot be defined, the specificity of the variable or neighbourhood boundary is not of great concern as we understand that this unidentified region sits in the top 10 regardless.

Ultimately, my analysis found that Toronto Police Services have not been successful in materially reducing the frequency of major crimes due to the fact that there is only minute, positional variance within the stratification of the 10 most affected neighbourhoods. Conversely, my analysis of least affected neighbourhoods brought to attention a pattern wherein the Toronto Police Service seem to be more effective at maintaining a low crime rate in a geographical area which *already* retains a low major crime frequency, as the variation is minimal. These results affirm

[1] I consider the top ten neighbourhoods in the first year of this data set, 2014, as the baseline for "high-risk" neighbourhoods, and measure any evidenced material change in deviation from these neighbourhoods punctuating the top 10 in the 5-year period thereafter.

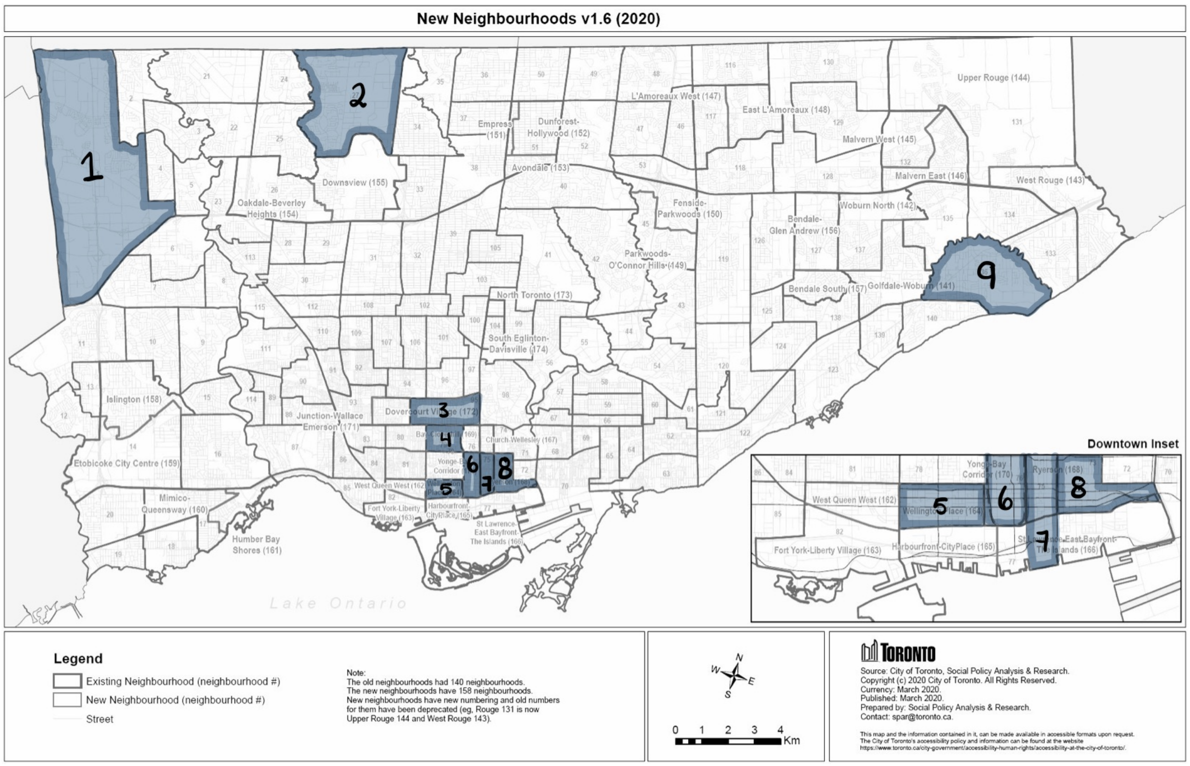

Figure 1: A map of the composition of neighbourhoods in Toronto, where nine of the top 10 high-risk neighbourhood are highlighted in blue.

the complex interplay of socio-economic conditions and violent crime, most notably assault; thus underscoring the absolute role of the embodiment of restorative justice within policing practices.

In the Data section, the acquisition of the Major Crime Indicators data set is discussed, as well as the data cleaning process applied to the data prior to initial analysis. The Results section follows with analyzing persistent patterns in major crime frequency from 2014 to 2023, inclusive, and examining the specific crime category of Assault to identify any subtle meaning within the data. The discussion section then synthesizes these analyses, concluding that there is no material reduction in major crime frequencies in high-risk neighbourhoods over the past decade. The paper concludes with a brief look into the broader socio-economic factors which contribute to the complex composition of major crime and thus overall crime rates.

2 Data

Data used in this paper was retrieved from the City of Toronto's Open Data Portal (Gelfand 2022) which is accessed through the Open Data Toronto online library. Open Data Toronto acquired their data from Toronto Police Services, who also originally collected the data. While data from the Toronto Police Services is heavily referenced and reproduced, it is important to consider that as police forces collect boundless amounts of data, we empirically know little "about the quality of the data coming into police data management systems" (O'Connor et al. 2022). However, there does also appear to be a positive relationship between police forces' active use of the data and caring about the quality of the data (O'Connor et al. 2022). The data source used is named `Major Crime Indicators` (Toronto Police Services 2024) which was retrieved to analyze major crime reports across Toronto geographical neighbourhoods, during the time period of 2014 to 2023, inclusive. The data was collected, cleaned and analyzed in the programming language `R` (R Core Team 2022). Supplementary libraries that were utilized during the analysis and compilation of the data set include `tidyverse` (Wickham et al. 2019), `knitr` (Xie 2023), `janitor` (Firke 2023), `dbplyr` (Wickham, Girlich, and Ruiz 2023), and `ggplot2` (Wickham 2016).

2.1 Frequency of Major Crime Indicators

To begin, I looked at the frequency of the five major crime indicators in Toronto during the period of 2014 to 2023, inclusive. There are 372,899 entries across the 10 year period.

I displayed the data in both absolute form, using the number of reports of each major crime indicator; and relative form as well, using the relative percentage of each major crime indicator.

Table 1: **Actual Portion of Each Crime Category**

Major Crime Category	Frequency	Percentage
Assault	197906	53.1
Auto Theft	58441	15.7
Break and Enter	70148	18.8
Robbery	33921	9.1
Theft Over	12483	3.3

As a comparison to the above Table 1, I have simulated the distribution of 372,899 random samples of major crimes, shown below. The differing assumption here for the simulation, is that each crime is equally likely, and sampled at random. Similar to how the data is portrayed above, I displayed the data in both absolute and relative form.

Table 2: **Simulated Portion of Each Crime Category**

Major Crime Category	Frequency	Percentage
Assault	74371	19.9
Auto Theft	74907	20.1
Break and Enter	74471	20.0
Robbery	74624	20.0
Theft Over	74526	20.0

The Law of Large Numbers states that when taking a very large number of independent and identical samples, the average of the results converges to the true value (Hsu and Robbins 1947). Since each of the five categories are equally likely to be chosen in the simulation, I expect that for a large sample size as conducted for the table above, each category's portion will converge to 20%.

Comparing the Table 1 and Table 2 of relative portions of major crimes, I observed that there is a significantly higher skew towards the number of actual assault reports, as the relative portion is over half of all major crime reports. Robbery and Theft Over [a certain dollar amount] have the largest negative deviations from the simulated values of 20%, in which the assumption was that all major crimes were equally likely and randomly chosen.

2.2 Progression of Major Crime Frequency

In the first section, I observed the frequency of major crimes over the time period in which the data was grouped by the five major crime indicators, which shed light on the major crime indicators that tend to occur more and less often.

Now, I will display the progression of the number of annual major crime reports made over the 10-year period. I used `ggplot2` (Wickham 2016) to generate Figure 2 with the years from 2014 to 2023, inclusive, in chronological order on the x-axis, which more clearly illustrates the trend of major crime occurrences over time.

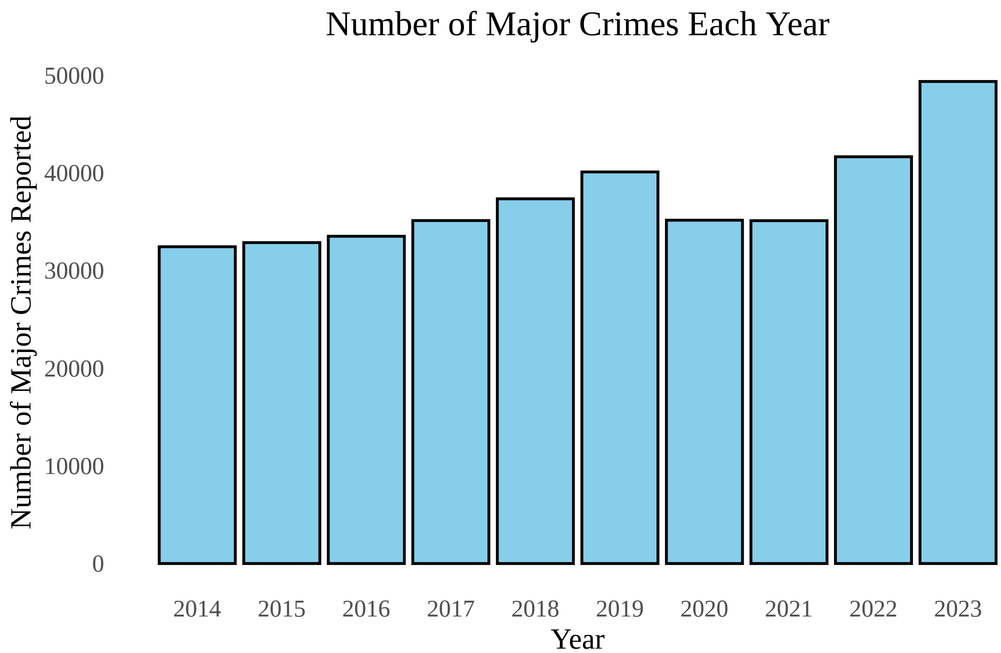

Figure 2: A bar graph is used to display the number of major crimes reported each year.

3 Results

3.1 Upper and Lower Tail Analysis of Neighbourhoods Affected By All Five Major Crimes

In this section, I will analyze the neighbourhoods **most** and **least** affected by all five major crime indicators. Then, in the following section, I will analyze the neighbourhoods most and least affected by violent crimes, namely only reported assaults.

For the time period of 2014 to 2023, inclusive, I compared the 10 neighbourhoods in which the most major crimes (MC) were reported in the former five years with the 10 most affected neighbourhoods in the latter five years, shown in Table 3 and Table 4 below.

Table 3: **Top 10 Neighbourhoods with Most MC Reported from 2014 to 2018**

Neighborhood	Number of MC
West Humber-Clairville	4646
Moss Park	3751
Yonge-Bay Corridor	3695
Wellington Place	3580
Downtown Yonge East	3350
York University Heights	3266
Kensington-Chinatown	3186
West Hill	2873
NSA	2528
Annex	2336
Total	33211

Table 4: **Top 10 Neighbourhoods with Most MC Reported from 2019 to 2023**

Neighborhood	Number of MC
West Humber-Clairville	5689
Moss Park	4890
Downtown Yonge East	4418
York University Heights	4003
Yonge-Bay Corridor	3619
Wellington Place	3381
Kensington-Chinatown	3363
NSA	3280
Annex	3145
West Hill	2868
Total	38656

Evidently, out of the 10 neighbourhoods most affected by major crimes in the former five years of the aforementioned time period, all 10 of those neighbourhoods appear again in the latter five years.

It is important to examine both ends of the neighbourhood crime spectrum to understand more about the distribution of reported crimes across Toronto neighbourhoods. Now I will observe whether the safest neighbourhoods in the former five years of the time period also remain the safest neighbourhoods in the latter five years, or if they differ materially.

Table 5: **The 10 Neighbourhoods with the Least MC Reported from 2014 to 2018**

Neighborhood	Number of MC
Centennial Scarborough	400
Casa Loma	399
Avondale	374
Mount Pleasant East	371
Guildwood	369
Woodbine-Lumsden	349
Markland Wood	346
Maple Leaf	300
Yonge-St.Clair	289
Lambton Baby Point	261
Total	3458

Table 6: **The 10 Neighbourhoods with the Least MC Reported from 2019 to 2023**

Neighborhood	Number of MC
Yonge-St.Clair	468
Bayview Woods-Steeles	450
Centennial Scarborough	446
Maple Leaf	443
Markland Wood	442
Old East York	434
Humber Heights-Westmount	399
Lambton Baby Point	330
Guildwood	319
Woodbine-Lumsden	309
Total	4040

I observed from the two tables above, that seven of the 10 neighbourhoods least affected by major crimes in the first half of the last decade also carry over as the least affected neighbourhoods in the second half of the last decade. This figure can be compared to the previously compiled number of all 10 of the 10 neighbourhoods most affected by major crimes also carrying over to the second half of the decade.

As an aside; I consulted ChatGPT 3.5 to assist in generating Table 3, Table 4, Table 5, and Table 6, along with the total in each table (OpenAI 2024).

3.2 Upper and Lower Tail Analysis of Neighbourhoods Affected By Violent Crimes (Assaults)

As stated in the prior section, I aimed to narrow my search to examine only violent crimes, namely assaults reported in each neighbourhood.

For the time period of 2014 to 2023, inclusive, I compared the 10 neighbourhoods in which the most assault crimes were reported in the former five years as shown in the above table, with the 10 most affected neighbourhoods in the latter five years, as shown below in Table 7 and Table 8.

Table 7: **Top 10 Neighborhoods with Most Assaults Reported from 2014 to 2018**

Neighborhood	Number of Assaults
Yonge-Bay Corridor	2584
Wellington Place	2543
Moss Park	2237
Downtown Yonge East	2076
West Hill	1988
Kensington-Chinatown	1924
York University Heights	1623
Glenfield-Jane Heights	1516
West Humber-Clairville	1507
NSA	1504
Total	19502

Table 8: **Top 10 Neighborhoods with Most Assaults Reported from 2019 to 2023**

Neighborhood	Number of Assaults
Moss Park	3210
Downtown Yonge East	2926
Yonge-Bay Corridor	2352
Wellington Place	2023
Kensington-Chinatown	2018
West Hill	1928
NSA	1869
York University Heights	1798
Church-Wellesley	1774
St Lawrence-East Bayfront-The Islands	1773
Total	21671

Table 8: **Top 10 Neighborhoods with Most Assaults Reported from 2019 to 2023**

Neighborhood	Number of Assaults

I deduced that out of the 10 neighbourhoods most affected by assault crimes in the former five years of the aforementioned time period, eight of those same neighbourhoods appear again in the latter five years.

Once again, we must examine both ends of the spectrum, and so I will display the results in Table 9 and Table 10 for the 10 neighbourhoods least affected by assaults in the first five years, and then the 10 neighbourhoods least affected by assaults in the latter five years of the last decade.

Table 9: **The 10 Neighbourhoods with the Least Assaults Reported from 2014 to 2018**

Neighborhood	Number of Assaults
Maple Leaf	139
Kingsway South	134
Edenbridge-Humber Valley	129
Lawrence Park North	128
Bridle Path-Sunnybrook-York Mills	127
Yonge-St.Clair	127
Princess-Rosethorn	122
Markland Wood	108
Lawrence Park South	101
Forest Hill South	92
Total	1207

Table 10: **The 10 Neighbourhoods with the Least Assaults Reported from 2019 to 2023**

Neighborhood	Number of Assaults
Lawrence Park North	182
Leaside-Bennington	181
Lambton Baby Point	176
Humber Heights-Westmount	175
Woodbine-Lumsden	172
Markland Wood	161

Table 10: **The 10 Neighbourhoods with the Least Assaults Reported from 2019 to 2023**

Neighborhood	Number of Assaults
Kingsway South	156
Lawrence Park South	152
Forest Hill South	148
Princess-Rosethorn	126
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Total	1629

I observed from Table 9 and Table 10 above, that six of the 10 neighbourhoods least affected by assaults in the first half of the last decade also carry over as the least affected neighbourhoods in the second half of the last decade. This figure can be compared to the previously compiled number of eight of the 10 neighbourhoods most affected by assaults also carrying over to the second half of the decade.

As an aside; I consulted ChatGPT 3.5 to assist in generating Table 7, Table 8, Table 9, and Table 10, along with the total in each table (OpenAI 2024).

3.3 Comparison of Results in Neighbourhoods Affected by All Major Crimes (MCs) and only Violent Crimes (VCs)

When comparing the progression of the 10 neighbourhoods most affected by major crimes (MCs) over the time period of 2014 to 2023, inclusive, to the 10 neighbourhoods least affected by MCs over the same time period, I noticed that while three of the least affected neighbourhoods in the first five years were replaced by other neighbourhoods whose MC rates reduced comparatively, this was not the case for neighbourhoods that were most affected by MCs.

While the ordering of the most affected neighbourhoods may have changed, the fact is that those same 10 neighbourhoods were still the most affected even in the latter five years of the time period.

A similar phenomenon occurred when comparing the progression of the 10 neighbourhoods most affected by violent crimes (VCs) to the 10 neighbourhoods least affected by VCs over the aforementioned time period. For neighbourhoods most affected by VCs, I found that only two neighbourhoods were replaced moving into the second half of the decade, whereas for neighbourhoods least affected by VCs, four of the neighbourhoods were replaced moving into the latter half of the decade.

From this, we can observe that for neighbourhoods in which major crime rates are already low, there is more variation in those neighbourhoods having their crime rates reduced comparatively to other neighbourhoods with similarly low crime rates, implying that police intervention may be more effective in affecting crime rates of generally safe neighbourhoods.

However, for neighbourhoods in which their major crime rates are already the highest, there is very little progression over the years in those neighbourhoods crime rates dropping comparatively to other neighbourhoods. Thus, there is very little evidence that Toronto Police are able to reduce the prevalence and frequency of major crimes occurring in the most affected neighbourhoods. In the next section, I will discuss possible causes of this data, and examine a possible relationship between crime rates and the Toronto Police Service's Operating Impact.

4 Discussion

Overall, I cannot say there has been a material reduction in the frequency of major crimes in high-risk Toronto neighbourhoods over the past 10 years. Though their stratification may differ, the 10 variable neighbourhoods which experience the highest frequency have remained the same from 2014 to 2023, inclusive. Socio-economic, political and cultural events of the last decade, and their intrinsic relationship with the nature of crime and policing may potentially explain the 17.6% raise in major crime indicators in 2023 (Lilley, n.d.).

It is certain that socio-economic and environmental factors contribute considerably to the temporal and spatial distribution of violent crimes. This is particularly true of urban areas, wherein an 'urban area' refers to a geographic area with socio-economic, demographic and built-environment characteristics which effect an informal separation from comparably affluent areas (Mohammadi et al., n.d.).

Considering this broader context, it is evident that the living impact of events such as the economic fluctuations; the COVID-19 pandemic; the Black Lives Matter Movement and responsive over-policing; and Trump-era weaponized political polarization and consequential social unrest (to name a few) all contribute to the complex composition of major crimes and thus overall crime rates.

We can specifically consider the 2020 social movement to de-fund police services across North America—-assuming Toronto Police Services were subject to de-funding, we can assume the effective trade-off becomes the exchange of over-policing for a significantly reduced operating impact (Rutland 2023). But just how much of an impact might this have on crime rates in Toronto neighbourhoods?

To analyze this relationship, I generated a graph, Figure 3, which measures the correlation between two variables. The first variable is the number of major crimes reported annually in Toronto, as shown in Figure 2. The second variable is the annual Total Projects Operating Impact for the Toronto Police Service. Each variable contains a single data value for each year in the 10-year time period of 2014 to 2023, inclusive.

In Figure 3 below, I consulted ChatGPT 3.5 to include the line of best fit and the calculated linear correlation coefficient (OpenAI 2024).

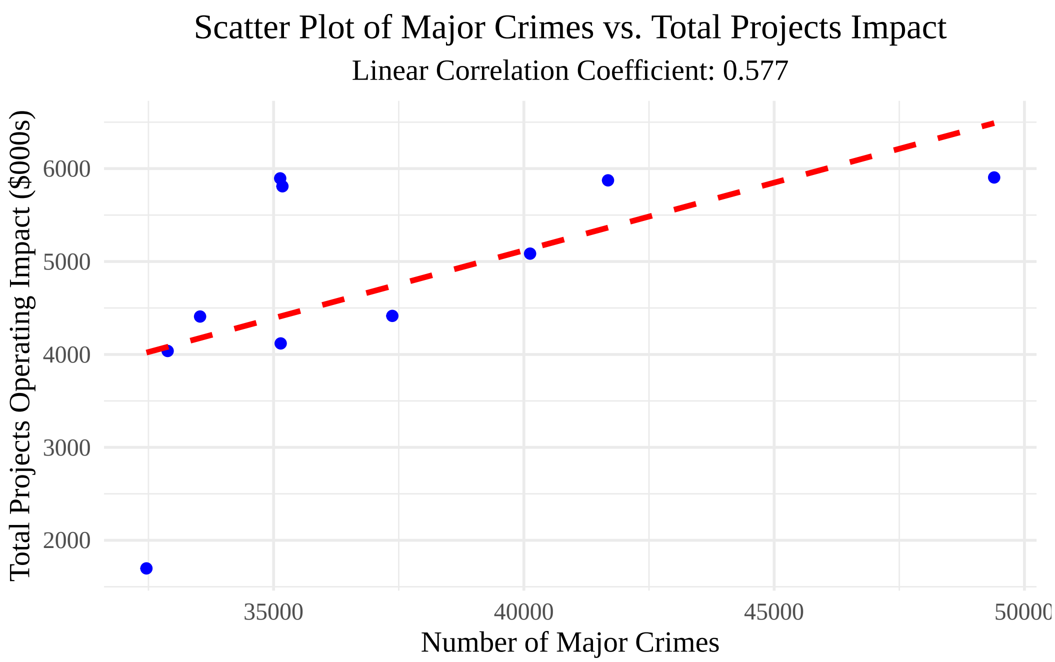

Figure 3: A scatter plot is used to display the relationship between the annual Total Projects Operating Impact for the Toronto Police Service, and the number of major crimes reported each year.

Based on the linear correlation coefficient of 0.577 between the two variables for the time period of 2014 to 2023, inclusive, one could hypothesize that a positive relationship exists between the annual number of major crimes reported in Toronto neighbourhoods and the Operating Impact for the Toronto Police Service.

However, it is important to remember that correlation does not imply causation; meaning that despite there being a moderately strong, positive relationship between these two variables, it is not necessarily true that higher crime rates are associated with higher Operating Impact for the police. As aforementioned, for broad data sets such as crime data for a metropolis like Toronto, there are many moving pieces and potential factors which may affect the crime rate in a given year.

For example, a naturally increasing population over time will consequently increase the number of crimes reported, all else remaining the same. As well, a lag in the City of Toronto's public policy may have a slower effect on impacting a meaningful reduction in the number of crimes occurring in Toronto neighbourhoods, which could mean that perhaps in the next five or 10 years, we may observe more material impacts in the reduction of major crimes or specifically violent crimes in high-risk neighbourhoods

Finally, it is also possible that a higher percentage of people who actually were assaulted ended up reporting the crime due to the severity of the crime, compared to other non-violent major crimes, which could suggest that the actual relative portions of non-violent crimes (Auto Theft, Break and Enter, Robbery, Theft Over) are higher than shown in the data in Table 1. With that being said, there is likely only a very small percentage of non-violent major crimes that went unreported, as the four other major crime indicators still represent severe crimes.

5 Conclusion

This paper analyzes the Toronto Police Services' success in materially reducing the frequency of major crime indicators in high-risk neighbourhoods across Toronto from 2014 to 2023, inclusive. Data analysis shows that the Toronto Police Service has **not** materially reduced the frequency of major crime indicators in the last 10 years, instead showing a correlation between crime rate variation and historically low-risk neighbourhoods. This correlation points to the unrest which exists in the bedrock of the top 10 high-risk neighbourhoods as a result of socio-economic, demographic and built-environment characteristics. This suggests that the complex systems which underscore police-reported crime and the performance of violent crime itself revolve deeply around large- and small-scale factors, events and phenomena, thus underscoring the desperation of the Toronto public to see the Toronto Police Services truly embody restorative justice within their policing practices.

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