Neighbourhood Crime in Toronto (2019–2024)*

Analyzing Crime Trends in Low, Medium, and High Socioeconomic Areas

Mike Cowan

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This paper examines how neighbourhood-level crime trajectories in Toronto evolved from 2019 through 2024, using socioeconomic clustering to identify crime rate divergence across 158 Toronto neighbourhoods. Drawing on data from the 2021 Canadian Census and the Toronto Police Service, we applied K-means clustering to group neighbourhoods into three socioeconomic categories reflecting relative socioeconomic advantage (High-, Medium-, and Low- Opportunity) and compared crime rates across these clusters over time. Across all four crime types, Low Opportunity neighbourhoods experienced persistently higher rates—especially for assault and shootings—while High Opportunity areas remained relatively insulated. Following a city-wide decline in break-and-enters during the 2020 lockdown, crime rebounded steeply in deprived areas, with robbery and gun violence disproportionately escalating through 2023. These findings highlight persistent socioeconomic disparities in crime exposure, with disadvantaged neighbourhoods bearing a disproportionate share of urban crime.

1 Introduction

The COVID-19 pandemic disrupted social and economic systems worldwide—and crime trends were no exception. In Canada, police-reported incidents plummeted in 2020 before rebounding sharply in 2021 (Statistics Canada, 2021), with violent crime surging 5% above pre-pandemic levels while property crime fell to historic lows.

However, these national trends obscure local disparities; crime clusters unevenly across urban spaces, concentrated in areas marked by structural inequities—e.g., income inequality, educational disparities, and labour market marginalization (Mohammadi et al., 2022; Wang et al., 2019). This spatial unevenness is particularly pronounced in Toronto, Canada's largest city,

*Code and data are available at: [https://github.com/mcowan38/tswd_toronto_crime].

where neighbourhoods diverge sharply in socioeconomic conditions—from affluent enclaves to zones of concentrated disadvantage (Jargowsky & Tursi, 2015).

To further examine these phenomena, this paper analyzes Toronto's neighbourhood-level crime trends during the pandemic and its aftermath. We analyze official crime counts for Toronto's neighbourhoods from 2019 through 2024, assessing how pre-existing social and economic inequalities relate to diverging crime trends. Specifically, we classify Toronto neighbourhoods into Low-, Medium-, and High-Opportunity clusters via K-means clustering on socioeconomic proxies and compare the crime trajectories of these clusters over time.

This paper proceeds as follows: First, we ground our analysis in criminological frameworks—i.e., social disorganization and strain—which help explain how neighbourhood opportunity structures (e.g., income, education, employment) may condition crime trends (Section 2). Next, we describe our data (Section 3) and model (Section 4), justifying our construction of neighbourhood opportunity clusters and analyzing their distinct crime trajectories from 2019 to 2024 (Section 5, with model diagnostics provided in Section A.1). We then consider what our neighbourhood-level results might suggest for understanding spatially differentiated crime dynamics in Toronto (Section 6). We conclude by discussing study limitations (Section 6.1).

2 Literature Review

Criminological theory and empirical evidence converge on two insights in urban crime literature: (1) neighbourhood-level structural conditions fundamentally shape crime, and (2) spatial inequalities between neighbourhoods amplify these effects.

Social disorganization theory suggests that poverty, residential instability, ethnic heterogeneity, and family disruption erode collective efficacy—the capacity of communities to enforce informal social controls. The resulting conditions create criminogenic environments where crime flourishes due to weakened guardianship-an institutional presence to deter crime-and institutional neglect (Antunes & Manasse, 2021; Frevel & Schulze, 2021). Strain theory complements this perspective, arguing that material deprivation and relative disadvantage generate frustration that may motivate criminal coping strategies, particularly during systemic crises-e.g., the COVID-19 pandemic (Antunes & Manasse, 2021).

More recent work highlights the importance of spatial inequality—the juxtaposition of affluence and deprivation across proximate neighbourhoods; inter-neighbourhood income disparities, rather than city-wide inequality alone, predict localized violence (Kang, 2016)-suggesting that proximity to wealth exacerbates perceptions of exclusion and strain (Uesugi & Hino, 2024; Wang et al., 2019). These findings align with contemporary research in Paterson, NJ, which suggests that median household income exerts the strongest neighbourhood-level influence on crime patterns (Yu & Fang, 2025).

Decades of evidence confirm that concentrated disadvantage—marked by poverty, unemployment, and single-parent households—correlates strongly with elevated crime rates (Frevel &

Schulze, 2021; Jargowsky & Tursi, 2015). Toronto exemplifies this dynamic: neighbourhoods with higher marginalization indices exhibit disproportionately high rates of violent and property crime (Wang et al., 2019), while areas with entrenched poverty report elevated homicide incidence (Mohammadi et al., 2022). However, the spatial heterogeneity of these relationships in major cities is also critical. For example, geographically weighted regression studies in Chicago (Arnio & Baumer, 2012) and Tokyo (Uesugi & Hino, 2024) reveal that the strength—and even the direction—of socioeconomic predictors of burglary or robbery vary across neighbourhoods.

The COVID-19 pandemic exposed and amplified these spatial inequities. Initial lockdowns reduced city-wide crime by diminishing routine activities, but declines in some cities were uneven (Andresen & Hodgkinson, 2022). For instance, while property crime in Vancouver decreased in wealthy neighbourhoods with robust security infrastructure, violent crime surged in disadvantaged areas strained by disrupted social services and weakened guardianship.

These patterns underscore three lessons: First, structural disadvantage predicts vulnerability to crime spikes during crises, aligning with social disorganization theory's emphasis on resource-deprived communities. Second, inter-neighbourhood inequality magnifies criminogenic risks, as strain theory posits when relative deprivation fuels frustration. Third, opportunity structures—e.g., access to security, institutional support, and economic stability—can be spatially stratified, privileging affluent areas with systemic advantages.

Building on these insights, we operationalize "opportunity" as relative access to stabilizing socioeconomic conditions—a small, composite measure proxied by median income, educational attainment, employment status, and household structure. Our analysis, focusing on Toronto neighbourhoods, compliments prior research in two ways: first, we expand the temporal scope to 2019–2024, assessing whether pandemic-era disparities persisted into the recovery phase. Second, we apply K-means clustering to classify neighbourhoods into High-, Medium-, and Low-Opportunity clusters using variables (income, education, employment) empirically shown to influence crime patterns (Yu & Fang, 2025). If social disorganization and strain theories hold, Low-Opportunity clusters should exhibit both higher baseline crime rates and greater volatility during disruptions, reflecting their structural precarity.

3 Data

We utilize the programming language Python (Python Core Team, 2019) alongside Polars (Vink & Polars Contributors, 2025) and scikit-learn (Pedregosa et al., 2011) for the paper's data cleaning and analysis.[1]

[1]The workflow and GitHub-based project structure follow best practices guided by Alexander (2023), which has proven to be an excellent resource: [https://tellingstorieswithdata.com].

3.0.1 Neighbourhood Crime Data

We sourced crime data from the Open Data Toronto Portal (The City of Toronto, 2025), which includes assaults, break-and-enters (B&E), robberies, and shootings—the types of crime we chose to analyze between 2019 and 2024. Crime rates per 100,000 persons were calculated by the City of Toronto using population estimates from Environics Analytics, in accordance with Statistics Canada's standard definition. Each entry includes incident years and total counts by neighbourhood (see Table 1).

Table 1: Toronto Crime Data (2014-2024)

	AREA_NAME	HOOD_ID	ASSAULT_2014	BREAKENTER_2014	...
0	South Eglinton-D	174	55	27	
1	North Toronto	173	53	25	
2	Dovercourt Villa	172	62	38	
3	Junction-Wallace	171	164	37	
4	Yonge-Bay Corrid	170	387	69	
...	...	...	...	...	...
153	West Humber-Clai	1	289	148	
154	Black Creek	24	222	26	
155	Pelmo Park-Humbe	23	58	30	
156	Humbermede	22	105	35	
157	Humber Summit	21	90	54	

Note. Table 1 previews Toronto Police crime data for 2014–2024. Columns include neighbourhood identifiers and annual counts of major crimes, truncated for display.

3.0.2 Neighbourhood Census Profiles

2021 Toronto Census Profile data was obtained from the Open Data Toronto Portal (The City of Toronto, 2025), which draws on Statistics Canada's Census of Population to compile selected demographic and socioeconomic indicators. We transformed a subset of these variables—originally aggregated to Toronto's 158 social planning neighbourhoods—to align with the neighbourhood identifiers used in the crime dataset (see Table 2).

Table 2: Toronto Neighbourhood Census Data (2021)

	Neighbourhood Name	West Humber	Mt. Olive	Thistletown	Elms-Old	...
0	Neighbourhood Number	1	2	3	5	
1	Total - Age groups of th	33300	31345	9850	9355	
2	0 to 14 years	4295	5690	1495	1610	

Table 2: Toronto Neighbourhood Census Data (2021)

	Neighbourhood Name	West Humber	Mt. Olive	Thistletown	Elms-Old	...
3	0 to 4 years	1460	1650	505	440	
4	5 to 9 years	1345	1860	540	480	
...	...	...	...	...	...	...
2597	Total - Eligibility and	3875	5540	1325	1520	
2598	Children eligible for	335	395	120	70	
2599	Eligible children wh	255	245	75	60	
2600	Eligible children wh	75	145	45	10	
2601	Children not eligible	3540	5145	1205	1445	

Note. Table 2 previews the 2021 Toronto Census dataset. Columns include standardized socioeconomic indicators (e.g., education rate, household income) across selected neighbourhoods. Names and values have been truncated for display.

3.1 Measurement

Transforming the realities of Toronto's neighbourhoods into data suitable for our analysis required two steps: (1) constructing a composite socioeconomic profile for each neighbourhood and (2) aggregating police-reported crime counts to rate units.

From the Census data, we extracted four attributes that decades of criminological research identify as correlates of neighbourhood crime: median household income, share of adults with a bachelor's degree or higher, unemployment rate, and proportion of single-parent families.

From the crime dataset, we aggregated annual counts of assaults, B&E, robberies, and shootings (2019–2024). Where population denominators were available, we converted raw counts into rates per 100,000 persons at the neighbourhood level. In instances where rate data were already provided, we retained the available figures without transformation.

These two sources were paired by Toronto's 158 neighbourhoods, yielding socioeconomic features and crime rates from the early pre-pandemic to post-pandemic periods.

4 Model

Cognizant of prior criminological studies—which have employed powerful spatial models to characterize neighbourhood heterogeneity in crime and socioeconomic conditions, utilizing substantially more predictors (Mohammadi et al., 2022; Uesugi & Hino, 2024; Wang et al., 2019; Yu & Fang, 2025)—we apply K-means clustering to four standardized indicators—education rate, proportion of single-parent households, unemployment rate, and median household income—to cluster neighbourhoods based on their socioeconomic similarity.

The K-means algorithm identifies the set of cluster centroids μ_k that minimizes the total within-cluster sum of squared distances (WCSS)[2]. In simple terms, the algorithm partitions observations into K groups such that data points within each group are as similar as possible to one another. Similarity is measured by the squared Euclidean distance between each observation and the average of its assigned group—called the cluster centroid. The goal is to find centroid locations that minimize the total variation within each cluster, producing compact and well-separated groups.

Let $\mathbf{x_i} = (x_{i1}, x_{i2}, x_{i3}, x_{i4})$ denote the four-dimensional vector of z-scored socioeconomic features for neighbourhood i, where $i = 1, \dots, N = 158$. Each vector includes standardized values for (1) median household income, (2) the proportion of residents with a bachelor's degree or higher, (3) the unemployment rate, and (4) the single-parent household rate.

Each raw feature is standardized by

$$x_{ij}^{\text{scaled}} = \frac{x_{ij} - \overline{x}_j}{s_j},$$

where $\overline{x}_j$ and s_j are the sample mean and standard deviation of feature j.

We then partition $\{\mathbf{x}_i\}_{i=1}^N$ into $K = 3$ clusters using the K-means algorithm, minimizing the WCSS:

$$\{\mu_k\}_{k=1}^3 = \arg\min_{\{\mu_k\}} \sum_{i=1}^{N} \left\| \mathbf{x}_i - \mu_{z_i} \right\|^2,$$

where μ_{z_i} is the centroid of neighbourhood i's assigned cluster.

We tested $K = 2, \dots, 5$ and selected $K = 3$ based on silhouette diagnostics (see Section A.1). Additionally, Principal Components Analysis—conducted as a diagnostic check—showed that the first two components explain ~89% of total variance, confirming a strong low-dimensional socioeconomic gradient underlying the four indicators.

We adopted a three-group classification—High, Medium, and Low Opportunity—aligned with standard socioeconomic strata commonly used in policy discourse and everyday language (i.e., upper, middle, and lower class). Based on this scheme, the resulting clusters are labelled as shown in Table 3 below.

[2]Mathematical notation adapted from Hastie et al. (2009).

Table 3: Descriptive Statistics by Opportunity Cluster (2019–2024)

Cluster	Neighbourhoods	Med. Income ($)	Single-Parent	Education	Unemployed (%)
0	19	132368.42	0.12	0.7	9.67
1	72	88775.0	0.15	0.58	12.75
2	67	76870.15	0.25	0.34	16.37

Note. Table 3 presents the average socioeconomic features by cluster for Toronto neigbourhoods over 2019–2024. Clusters were derived via K-means clustering on standardized education rate, proportion of single-parent households, unemployment rate, and median household income. High-Opportunity (Cluster 0) neighbourhoods exhibit high educational attainment and median income alongside low unemployment and single-parent household rates. Medium-Opportunity (Cluster 1) neighbourhoods display a mixed socioeconomic profile. Low-Opportunity (Cluster 2) neighbourhoods are characterized by lower education and income, and higher unemployment and single-parent household rates. All values represent means of each indicator across the period of study.

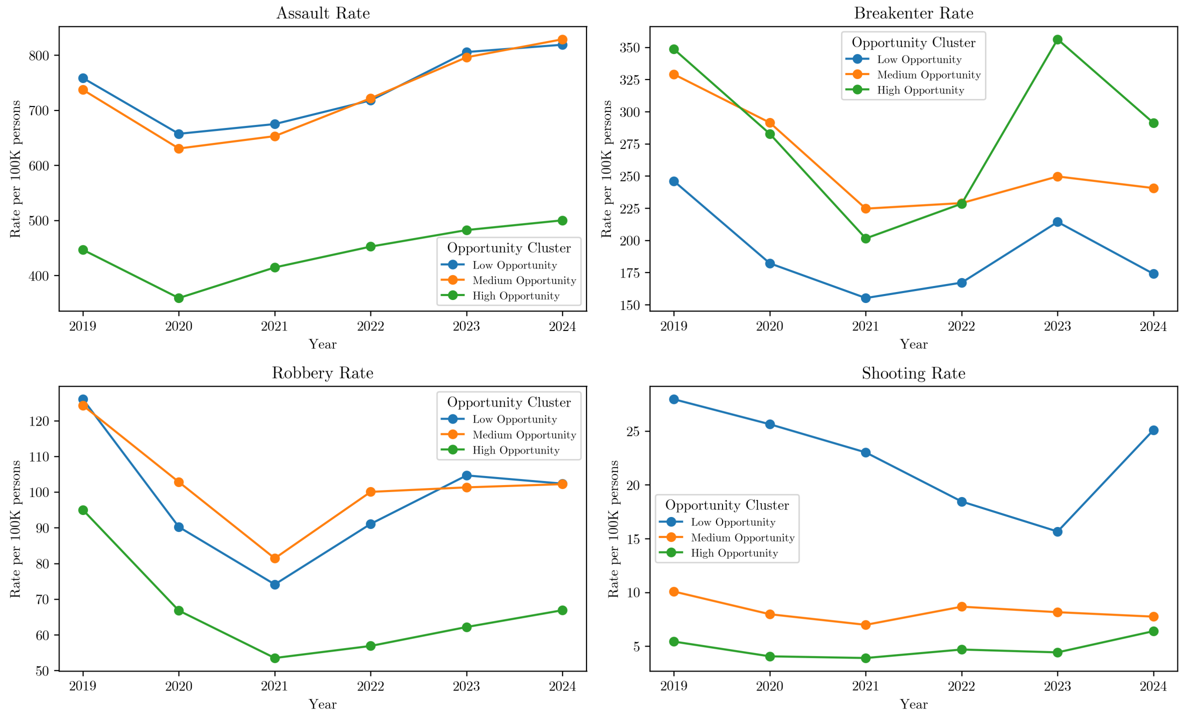
Although we also explored Gaussian Mixture Models (GMM)[3]—which relax the spherical cluster assumption imposed by K-means (Pedregosa et al., 2011), we retained the K-means technique due to its superior evaluation scores and greater interpretability (both methods produced broadly similar neighbourhood groupings; see Figure 2).

5 Results

Our results are summarized in Figure 1.

[3]GMM models the data as a mixture of K multivariate normal distributions, estimating a mean vector and covariance matrix for each component.

Figure 1: Average Crime Rate Trends by Socioeconomic Cluster (2019–2024)



Note. Figure 1 plots trends in crime rates for Assault, Break-and-Enter, Robbery, and Shootings. For each year and crime type, the figure shows the mean rate across all neighbourhoods within each cluster.

Figure 1 illustrates how crime unfolded across Toronto's neighbourhoods between 2019 and 2024. In Low-Opportunity neighbourhoods, assault rates edged upward from 758 to 805 incidents per 100,000 persons—an increase of 6.2%—while Medium-Opportunity areas saw an 8.0% rise, from 737 to 796 per 100,000. Even High-Opportunity neighbourhoods experienced a modest 8.0% uptick in assaults, climbing from 446 to 482 per 100,000.

By contrast, the divergence between neighbourhood type and violent crimes is more pronounced. Robbery rates in High-Opportunity areas decreased by roughly one-third (a 34.5% reduction), falling from 95 to 62 per 100,000, whereas Low-Opportunity clusters recorded a smaller decline of 16.9% (126 → 104). Medium-Opportunity wards registered an 18.5% drop (124 → 101). Shooting incidents fell most dramatically in Low-Opportunity areas—dropping from 27.95 to 15 per 100,000, a 44.0% decrease—while Medium- and High-Opportunity neighbourhoods saw reductions of 19.0% (10 → 8) and 18.5% (5 → 4), respectively.

The 2020 city-wide dip in B&Es—driven, in part, by greater residential presence—was particularly deep in deprived areas, where rates fell 26.0% from 246 to 182 per 100,000 between 2019 and 2020. However, by 2023, Low-Opportunity wards had rebounded to 214 incidents per

100,000—just 12.9% below their pre-pandemic level. Medium-Opportunity neighbourhoods saw a more sustained decline, with B&E down 24.1% (329 → 249), while High-Opportunity areas only edged 2.2% above 2019 levels (348 → 356)[4].

6 Discussion

Adopting a three-cluster solution revealed noticeable patterns that would be obscured by a binary split (specifically, $K = 2$; see Section A.1), underscoring the value of an intermediate socioeconomic category. While Low-Opportunity neighbourhoods began the pre-pandemic period with higher baseline crime as was expected, the Medium-Opportunity cluster exhibited dynamic behaviour, pairing with High- and Low-Opportunity trajectories depending on crime type.

Low- and Medium-Opportunity areas displayed similar rates of year-to-year change across all crime types (with the exception of B&E): a sharp decline during the 2020 lockdown, followed by a steady rise from 2022 to 2023. This suggests a shared vulnerability once a threshold of concentrated disadvantage is crossed, in alignment with social disorganization theory (Antunes & Manasse, 2021; Frevel & Schulze, 2021). Weakened collective efficacy and disrupted informal social controls likely triggered uniform social breakdown across these areas, of their relative positions on the socioeconomic spectrum.

In contrast, robbery crimes showed a similar arc across all clusters-dipping during the lockdown and rebounding post-2021-but the steepest uptick occurred in Low-Opportunity areas, closely followed by Medium-Opportunity zones. This erosion of distinction implies that mounting economic strain and institutional disengagement can rapidly intensify motivations for acquisitive crime in disadvantaged neighbourhoods (Antunes & Manasse, 2021). Noticeably, High-Opportunity neighborhoods remained relatively insulated, showing only modest growth post-lockdown.

B&E crime rates diverged sharply in the years following the pandemic. While all clusters had declined substantially-Medium- and High-Opportunity largely areas moved in tandem-High-Opportunity neighbourhoods experienced a significant spike, surpassing their 2019 rates. This spike likely reflects shifts in routine activity patterns: as residents of affluent areas returned to in-person work and travel, homes were left unoccupied more frequently, reducing natural guardianship and increasing opportunities for property crime.

Lastly, shootings were equally low in Medium-Opportunity and High-Opportunity neighbourhoods, both maintaining relatively flat trajectories from 2019 to 2024. In stark contrast, however, Low-Opportunity areas—where the majority of the crimes appear to have occurred—experienced a sharp surge in 2023.

[4]See Table 3 for the breakdown of the year-to-year rate change.

Social disorganization theory helps to explain the persistent vulnerability of disadvantaged areas (Antunes & Manasse, 2021; Frevel & Schulze, 2021). Concentrated disadvantage erodes collective efficacy and informal controls, hindering the ability to sustain safety gains during and after shocks—such as the lockdown (Jargowsky & Tursi, 2015).

These theoretical dynamics are reflected in the observed post-pandemic trends. The rapid rebound in property crime and sustained elevation of violent crime in Low-Opportunity areas, alongside upward trends in Medium-Opportunity zones (robbery and shootings, albeit less intensely), also could reflect this diffusion of strain-related pressures (Yu & Fang, 2025). Furthermore, strain theory clarifies the steep post-2020 rise in robbery and shootings within Low-Opportunity clusters (Antunes & Manasse, 2021). Cumulative stressors—economic hardship, institutional disengagement, perceived exclusion—amplified by the pandemic likely intensified motivations for these crimes.

The widening gap between Low- and High-Opportunity clusters, especially for robbery and gun violence, signals deepening intra-urban inequality and intensifying crime concentration in the most vulnerable areas (Mohammadi et al., 2022; Uesugi & Hino, 2024).

6.1 Limitations

This study has several data-oriented limitations. First, our analysis is ecological in nature, drawing conclusions from neighbourhood-level aggregates rather than individual-level data. As such, we cannot determine whether individuals with certain socioeconomic characteristics are more likely to experience or perpetrate crime; we can only observe area-level patterns.

Second, the analysis relies solely on police-reported crime data, which are subject to well-documented limitations. Not all crimes are reported to law enforcement, and fluctuations in patrol coverage, resource allocation, or surveillance infrastructure can artificially inflate or deflate recorded incidents. These reporting inconsistencies likely vary across neighbourhoods, potentially skewing cross-area comparisons.

Additionally, the socioeconomic data we use are static, drawn from the 2021 Census. These indicators—income, education, unemployment, and single-parent status—cannot capture changes that occurred before or after 2021. Moreover, we excluded several potentially important variables—such as neighbourhood ethnic composition, immigration status, and residential mobility—which may shape both crime exposure and neighbourhood opportunity in substantive ways. As a result, our clustering captures only a partial view of structural disadvantage.

Fourth, our method for grouping neighbourhoods—K-means clustering—makes simplifying assumptions. It treats all four variables as equally important and assumes the clusters are roughly circular and evenly sized when, in reality, socioeconomic differences are rarely tidy

(Pedregosa et al., 2011). Alternative clustering methods that do not require an *a priori* estimation of K groups (e.g., MAP-DP; see Raykov et al., 2016) may better ascertain the true structure of the data.

Future research should address these gaps by using dynamic, multi-year socioeconomic data, incorporating a broader range of variables, and accounting for spatial relationships between neighbourhoods. In addition, combining quantitative patterns with qualitative accounts of neighbourhood residents could also help ground the numbers in the lived experiences of residents.

A Appendix

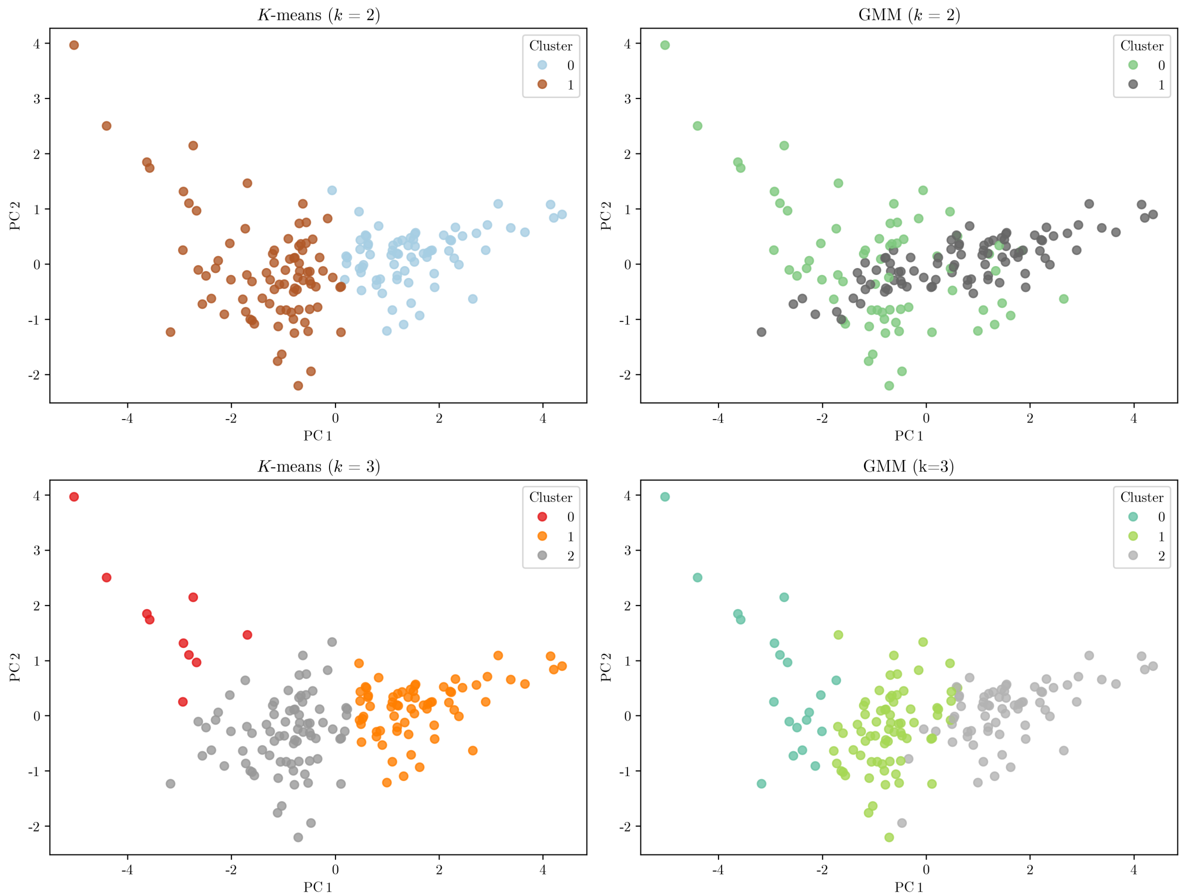
A.1 Model Evaluation

A.1.1 Cluster Plots

A choice of socioeconomic index can meaningfully shift the resulting clusters. One straightforward approach is to standardize each indicator (e.g., income, education, unemployment) to z-scores and sum them (Vyas & Kumaranayake, 2006). Alternatively, factor analysis, which derives weights from latent dimensions (e.g., “Economic Capital” or “Family Stability”), can better reflect the structure among variables but requires more complex modelling and larger samples.

Given that our inquiry is exploratory, we opted to employ K-means. Figure 2 reduces our data to the first two principal components for visualization purposes. To guard against algorithmic artifacts, we place K-means—characterized by hard, spherical boundaries—alongside Gaussian Mixture Models, which allow for soft, ellipsoidal groupings (Pedregosa et al. (2011)). Consistency across both models strengthens confidence that the identified neighbourhood clusters reflect meaningful socioeconomic divisions—and that our clustering choice was appropriate.

Figure 2: Clustering Techniques Comparison ($K = 2, 3$)



Note. Figure 2 displays the two-dimensional projection of neighbourhoods, coloured by assigned cluster. At $K = 3$, GMM's middle component (Cluster 1) overlaps with the Cluster 2, suggesting less clear separation at three clusters. Visually, K-means ($K = 3$) appears to be the superior model choice.

A.1.2 Evaluation Metrics

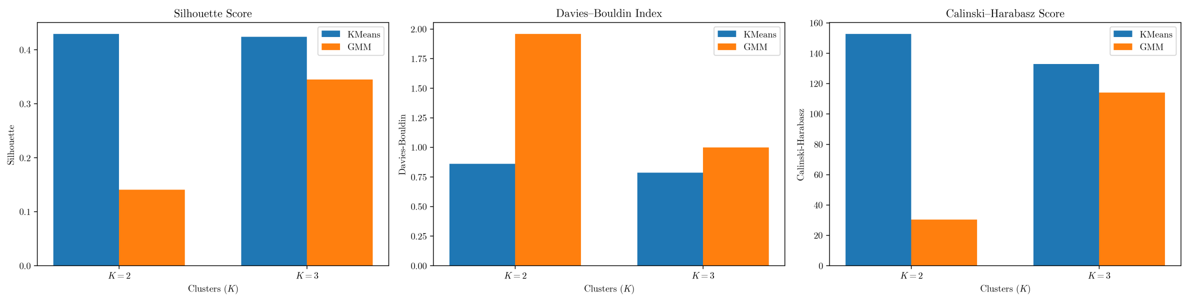
Figure 3 presents a detailed comparison of clustering quality across K-means and Gaussian mixture models[5]. We compute the Silhouette Score (ranging from -1 to 1; higher values indicate better cohesion and separation) to assess how closely each point is matched to its own cluster versus the next best alternative. The Davies–Bouldin Index measures the average similarity between each cluster and its most similar counterpart—lower values denote more

[5]Code and evaluation metrics more detail can be found in scikit-learn documentation (Pedregosa et al., 2011).

compact, well-separated clusters. Finally, the Calinski–Harabasz Score quantifies the ratio of between-cluster dispersion to within-cluster dispersion—higher scores signify clearer, more distinct groupings.

The clustering plots below help illustrate our choice of K-means with $K = 3$, which offers clearer group separation and a more stable cluster structure. In the K-means panels, the groupings are relatively distinct—particularly at $K = 3$, where clusters are well-separated across the principal component space. By contrast, the Gaussian Mixture Model results show less defined boundaries; at both values of K (especially $K = 2$), there is greater overlap between adjacent clusters and less visual separation-aligning with GMM's lower Silhouette and higher Davies–Bouldin Index values (see Figure 3).

Figure 3: Clustering Evaluation Metrics (K-means vs. Gaussian)



Note. Figure 3 displays three cluster-validation metrics for both K-means and Gaussian Mixture Models (GMM) at $K = 2$ and $K = 3$. For $K = 2$, GMM yields a Silhouette Score of 0.141, a Davies–Bouldin Index (DBI) of 1.958, and a Calinski–Harabasz Score (CHS) of 30.4, whereas K-means achieves 0.429, 0.860, and 152.7, respectively. Increasing to $K = 3$ improves separation for GMM (Silhouette = 0.345; DBI = 0.998; CHS = 114.1) but slightly reduces cohesion for K-means (Silhouette = 0.424; DBI = 0.786; CHS = 133.0).

While $K = 2$ yields a slightly higher Calinski–Harabasz Score (152.7 vs. 133.0), its gain in cluster compactness comes at the expense of interpretability: the two-group solution collapses meaningful socioeconomic variation between middle- and high-income neighbourhoods into a single cluster. In practical terms, the difference between the average median income of the two upper clusters ($132,368.42 vs. $88,775.00) is substantial and justifies treating them as analytically distinct.

A.1.3 Average Yearly Crime Rate Change by Neighbourhood Opportunity Cluster

A.1.3.1 Neighbourhood Assault

Table 4: Assault Rate Change by Cluster

	Year	Low Opportunity	Medium Opportunity	High Opportunity
0	2019	758.4	737.0	446.7
1	2020	657.2 (-13.3)	630.5 (-14.5)	359.1 (-19.6)
2	2021	674.8 (+2.7)	652.9 (+3.6)	414.6 (+15.5)
3	2022	717.8 (+6.4)	721.7 (+10.5)	452.4 (+9.1)
4	2023	805.6 (+12.2)	796.0 (+10.3)	482.4 (+6.6)
5	2024	818.8 (+1.6)	828.7 (+4.1)	500.1 (+3.7)

Note. Table 4 reports the 2019 baseline assault rate and year-over-year percent changes (2020–2024) for each cluster.

A.1.3.2 Break-and-Enter

Table 5: Break-and-Enter Rate Change by Cluster

	Year	Low Opportunity	Medium Opportunity	High Opportunity
0	2019	246.0	329.0	348.6
1	2020	182.2 (-26.0)	291.5 (-11.4)	282.8 (-18.9)
2	2021	155.2 (-14.8)	224.7 (-22.9)	201.5 (-28.7)
3	2022	167.2 (+7.7)	229.0 (+1.9)	228.5 (+13.4)
4	2023	214.3 (+28.2)	249.7 (+9.0)	356.3 (+55.9)
5	2024	174.0 (-18.8)	240.6 (-3.6)	291.2 (-18.3)

Note. Table 5 reports the 2019 baseline break-and-enter rate and annual percent changes.

A.1.3.3 Robbery

Table 6: Robbery Rate Change by Cluster

	Year	Low Opportunity	Medium Opportunity	High Opportunity
0	2019	126.0	124.3	95.0
1	2020	90.2 (-28.4)	102.8 (-17.3)	66.8 (-29.7)
2	2021	74.1 (-17.8)	81.4 (-20.8)	53.5 (-19.9)
3	2022	91.1 (+22.9)	100.1 (+22.9)	56.9 (+6.3)
4	2023	104.7 (+14.9)	101.3 (+1.3)	62.2 (+9.3)
5	2024	102.4 (-2.2)	102.2 (+0.9)	66.9 (+7.6)

Note. Table 6 reports the 2019 baseline robbery rate and annual percent changes.

A.1.3.4 Shooting

Table 7: Shooting Rate Change by Cluster

	Year	Low Opportunity	Medium Opportunity	High Opportunity
0	2019	28.0	10.1	5.4
1	2020	25.6 (-8.3)	8.0 (-20.9)	4.1 (-25.2)
2	2021	23.0 (-10.2)	7.0 (-12.4)	3.9 (-3.8)
3	2022	18.4 (-19.8)	8.7 (+24.1)	4.7 (+20.2)
4	2023	15.7 (-15.1)	8.2 (-5.9)	4.4 (-5.7)
5	2024	25.1 (+60.3)	7.8 (-5.1)	6.4 (+44.5)

Note. Table 7 reports the 2019 baseline shooting rate and subsequent annual percent changes for each cluster.

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