Structural Inequality and Gun Violence in NYC: A Census Tract Analysis Using PCA

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Abstract

Gun violence in New York City (NYC) is highly concentrated in neighbourhoods marked by socioeconomic disadvantage, yet few studies have examined how structural conditions shape shootings at the census tract level. This study applies Principal Components Analysis (PCA) and Spatial PCA (sPCA) to develop theory-informed indices of concentrated disadvantage and residential instability using 2019–2023 American Community Survey data, and models their association with NYPD-recorded shootings over the same period. Results from Negative Binomial Regression show that concentrated disadvantage is a strong and consistent predictor of shootings. Residential instability, however, proved weaker and less conceptually coherent, with indicators (e.g., foreign-born population) reflecting stability in some urban contexts. Incorporating spatial structure through sPCA reduced residual spatial clustering but weakened overall model performance. Findings underscore the utility of PCA in summarising neighbourhood conditions, while highlighting the contextual limitations of standard indices and the complexities of spatial modelling in diverse urban environments.

GitHub Repository:
https://github.com/darragh-mcgee/DimensionalityReduction/NYC_Shootings_PCA

1 Introduction

Gun violence is a public health epidemic in the United States, resulting in nearly 45,000 deaths and approximately 76,000 nonfatal injuries each year (Centers for Disease Control and Prevention, 2023). While it affects communities across the country, firearm violence is disproportionately concentrated in socioeconomically disadvantaged neighbourhoods and among marginalised populations (Boschan & Roman, 2024; Weisburd et al., 2004). These structural conditions frequently overlap and cluster geographically, creating environments of cumulative inequality where shootings are more likely to occur. In fact, 26% of U.S. firearm homicides occur in census tracts that contain just 1.5% of the population, underscoring the extreme spatial concentration of violence (Aufrichtig et al., 2017).

Although individual-level risk factors such as age, gender, and criminal history are well established, recent research has shifted toward neighbourhood-level predictors of violence. Structural conditions like concentrated disadvantage, residential instability, and historic segregation have been shown to shape the spatial distribution of firearm violence (Sampson et al., 2002; Peterson & Krivo, 2010).

To capture these dynamics, researchers frequently construct composite indices from socioeconomic and housing-related indicators. While some studies use additive indices or examine variables independently, others apply principal components analysis (PCA) to reduce dimensionality and capture underlying latent structures (Mears & Bhati, 2006).

Despite these advances, much of the literature aggregates shootings at the precinct or ZIP-code level, potentially obscuring meaningful variation at smaller spatial scales. New York City (NYC) presents a compelling case for tract-level analysis: its stark socioeconomic inequalities and racial segregation produce sharp contrasts between neighbouring census tracts. Yet relatively few studies apply dimensionality-reduction techniques like PCA at this level of geographic precision.

This study addresses that gap by investigating whether latent dimensions of concentrated disadvantage and residential instability are associated with the distribution of shooting incidents across NYC census tracts. It further examines whether incorporating spatial dependence into predictor construction improves our understanding of neighbourhood-level variation in gun violence.

2 Literature Review

2.1 Concentrated Disadvantage

Concentrated disadvantage refers to the spatial clustering of structural hardship within neighbourhoods, encompassing multiple forms of socioeconomic deprivation (Sampson & Wilson, 2013). Studies commonly use composite indices to capture concentrated disadvantage, frequently applying PCA to reduce correlated census variables into a single latent dimension (Mears & Bhati, 2006). These indices typically integrate data on welfare receipt, poverty, unemployment, female-headed households, child density, and educational disadvantage. These indicators have been shown to load strongly onto a single factor in urban settings, with core measures such as welfare receipt, poverty, and unemployment showing loadings above 0.85 (Sampson, Sharkey, & Raudenbush, 2008).

Disadvantaged neighbourhoods are marked by limited access to education, employment, and institutional resources, creating conditions that undermine social cohesion and elevate exposure to violence (Sampson, Raudenbush, & Earls, 1997). Empirical research consistently links concentrated disadvantage to elevated rates of violent crime, including shootings (Peterson & Krivo, 2010). For instance, Morenoff, Sampson, and Raudenbush (2001) found that communities with high levels of disadvantage experienced significantly more homicides, even after controlling for demographic factors.

2.2 Residential Instability

Residential instability refers to a high rate of population turnover within a neighbourhood, which can disrupt social cohesion and informal social control processes. It is commonly operationalised using indicators such as residential mobility, renter occupancy, housing vacancy, foreign-born population, and overcrowding (Krivo, Peterson, & Kuhl, 2009). As with concentrated disadvantage, residential instability is commonly measured using a composite index, with PCA frequently applied to extract a single latent dimension from related indicators. However, definitions and relevant indicators may vary across contexts; for instance, renter occupancy may signal instability in suburban or rural areas but may be less meaningful in high-density urban settings where renting is normative.

High levels of residential instability are associated with weakened local social networks and diminished informal social control. Bellair (1997) found that residential turnover disrupted social interaction, reducing the community's capacity to regulate behaviour and increasing the risk of violent crime. Sampson, Raudenbush, and Earls (1997) similarly showed that instability erodes collective efficacy, leading to higher rates of violent crime.

2.3 Spatial Dimensions of Inequality and Violence

Extensive research has demonstrated that both concentrated disadvantage and residential instability exhibit strong spatial patterning, shaped by historical processes of segregation, exclusionary housing policy, and urban disinvestment (Peterson & Krivo, 2010; Sampson, 2012). As a result, structurally disadvantaged neighbourhoods often cluster in close geographic proximity, forming pockets of entrenched inequality.

Similar spatial dynamics are evident in patterns of gun violence. Research consistently shows that shootings are disproportionately concentrated in disadvantaged neighbourhoods and clustered in persistent hotspots, driven by mechanisms such as retaliatory violence, social network diffusion, and institutional neglect (Boschan & Roman, 2024; Papachristos et al., 2015; Weisburd et al., 2004). This clustering is shaped not only by local dynamics but also by spillover effects, as violence and structural conditions extend beyond administrative boundaries (Sampson, 2012; Papachristos et al., 2012).

3 Theoretical Argument

This analysis and its hypotheses are grounded in established theoretical frameworks that explain the distribution of violence across urban neighbourhoods.

3.1 Neighbourhood Effects Theory

Neighbourhood Effects Theory suggests that sustained structural hardship undermines prosocial behaviour and increases vulnerability to violence through chronic stress, trauma, and constrained opportunity (Wilson, 1987; Sampson & Wilson, 1995). Neighbourhoods characterised by concentrated disadvantage are therefore more likely to experience elevated levels of violence due to the cumulative effects of economic dislocation, institutional neglect, and weakened social cohesion.

Hypothesis 1: *Census tracts characterised by higher levels of concentrated disadvantage will experience higher rates of shooting incidents.*

3.2 Social Disorganisation Theory

Social Disorganisation Theory proposes that population turnover disrupts local networks, weakens informal social control, and reduces residents' ability to collectively maintain order (Shaw & McKay, 1942; Sampson et al., 1997). In neighbourhoods marked by high residential instability, frequent movement undermines trust, reduces neighbourly interaction, and limits the formation of long-term social ties. As a result, informal mechanisms of control break down, increasing the likelihood of violent incidents.

Hypothesis 2: *Census tracts with greater residential instability will experience higher rates of shooting incidents, independent of disadvantage.*

3.3 Spatial Criminology and Diffusion

Spatial criminology highlights that neighbourhood violence is influenced by nearby areas and can diffuse across space through mechanisms such as retaliatory incidents and overlapping social networks (Papachristos et al., 2015). The tendency for neighbouring areas to exhibit similar patterns (i.e. spatial autocorrelation) is a well-documented characteristic of urban violence (Dalve et al., 2021). This spatial dependence suggests that measures of disadvantage and instability may underestimate their effects if geographic context is ignored (Dalve et al., 2021).

Hypothesis 3 (Exploratory): *Accounting for spatial autocorrelation in latent measures of concentrated disadvantage and residential instability will improve the prediction of census tract–level shooting rates.*

4 Methodology

4.1 Data

This study uses tract-level data to examine the relationship between structural neighbourhood characteristics and shooting incidents in NYC. Socioeconomic, housing, and demographic indicators were drawn from the 2019–2023 American Community Survey (ACS) five-year estimates, aggregated at the census tract level (N = 2,227). Shooting incident data for the same period were obtained from the NYC OpenData NYPD Historic Shooting Incident database, which includes geographic coordinates for each reported event.

Each incident was assigned to a census tract using spatial joins with U.S. Census Bureau shapefiles, yielding a tract-level count of total shootings over the five-year period. Eleven tracts with extremely small populations (¡100 residents) were excluded to reduce the influence of unstable rates in sparsely populated areas. The final analytical sample included 2,216 census tracts and 7,714 shooting incidents.

4.2 Dependent Variable

The dependent variable is the total number of shooting incidents recorded in each census tract between 2019 and 2023. To account for variation in population size across tracts, a log-transformed population offset was included in all regression models. This enables interpretation in terms of per capita shooting rates, improving comparability across neighbourhoods.

4.3 Independent Variables

Two theory-derived latent constructs were created to capture neighbourhood-level structural risk. Concentrated disadvantage was operationalised using six indicators: the percentage of individuals living below the poverty line, households receiving Supplemental Nutrition Assistance Program (SNAP) benefits, unemployment rate, percentage of female-headed households, proportion of the population under 18, and adults without a high school diploma. Residential instability was measured using four variables: proportion of renters, housing vacancy rate, percentage of foreign-born residents, and recent residential mobility. All variables were derived from ACS microdata and converted to proportions to allow for comparison across census tracts.

4.4 Ecological Controls

Ecological covariates were included in all models to account for neighbourhood demographic composition. The percentage of Black residents was included as a sociological control, reflecting its frequent inclusion in structural models of violence due to its association with systemic disadvantage, residential segregation, and inequality in urban settings (Peterson & Krivo, 2010). The percentage of males aged 15 to 29 was also included to capture demographic vulnerability, as this group is statistically the most likely to be involved in both the perpetration and victimisation of gun violence (Sampson et al., 2005).

4.5 Analytical Strategy

4.5.1 Principal Components Analysis (PCA)

To reduce multicollinearity and summarise correlated indicators into composite indices, separate PCA was conducted for concentrated disadvantage and residential instability. Variables were standardised prior to extraction to ensure comparability across indicators measured on different scales. Component retention was informed by eigenvalues greater than one, scree plot inspection, and interpretability of factor loadings. In both cases, the first principal component (PC1) was retained.

4.5.2 Spatial Principal Component Analysis (sPCA)

To assess whether latent structural conditions were spatially patterned, spatial PCA (sPCA) was applied to the same variable sets used in standard PCA. sPCA incorporates spatial weights into the dimensionality reduction process, extracting components that maximize both variance and spatial autocorrelation (Jombart et al., 2008). This helps identify geographically coherent structural patterns that may be missed by standard PCA, which assumes spatial independence.

4.5.3 Model Specification

Negative binomial regression was used to model the count of shooting incidents per census tract, due to evidence of overdispersion in the data. An initial Poisson model produced a dispersion ratio of 4.12, violating the Poisson assumption of equidispersion and justifying the use of a negative binomial approach.

The main specification included principal components representing *concentrated disadvantage* and *residential instability*, derived via standard PCA. Covariates for the percentage of males aged 15 to 29 and the percentage of Black residents were included, as outlined in the previous section. Robust standard errors were applied to correct for heteroskedasticity and enhance the reliability of statistical inference. The model is specified as follows:

$$\begin{aligned}\log(\mathbb{E}[\text{Shootings}_i]) = \beta_0 &+ \beta_1\,\text{ConcentratedDisadvantage}_i + \beta_2\,\text{ResidentialInstability}_i \\ &+ \beta_3\,\%\text{BlackResidents}_i + \beta_4\,\%\text{Aged15-29}_i + \log(\text{Population}_i) \quad (1)\end{aligned}$$

Appendix A provides a detailed description of the variables and covariates included in the model.

Following estimation of the PCA-based model, spatial autocorrelation in residuals was assessed using Moran's I. The result (Moran's I = 0.021, $p = 0.037$) indicated a modest but statistically significant degree of spatial dependence, suggesting some spatial patterning remained unexplained.

To address this, a second model was estimated using spatially structured predictors derived via sPCA. This allowed for a direct comparison of predictive performance between PCA- and sPCA-based models.

5 Results

5.1 Principal Component Analysis (PCA)

5.1.1 Concentrated Disadvantage

The PCA for concentrated disadvantage produced a first principal component (PC1) that explained approximately 54% of the variance (eigenvalue = 3.26). All six indicators loaded positively and in line with theoretical expectations (see Table 1).

Table 1: Principal Component Loadings for Concentrated Disadvantage

Indicator	**PC1 Loading**
% Below Poverty Line	0.856
% Receiving SNAP	0.883
% Unemployed	0.623
% Female-Headed Households	0.741
% No High School Diploma	0.701
% Aged Under 18	0.568

This pattern suggests that PC1 captures a well-defined latent dimension of socioeconomic deprivation. The strength and directional consistency of the loadings support the interpretation of PC1 as a meaningful summary measure of concentrated disadvantage.

Figure 1 presents a choropleth map of PC1 scores for concentrated disadvantage.

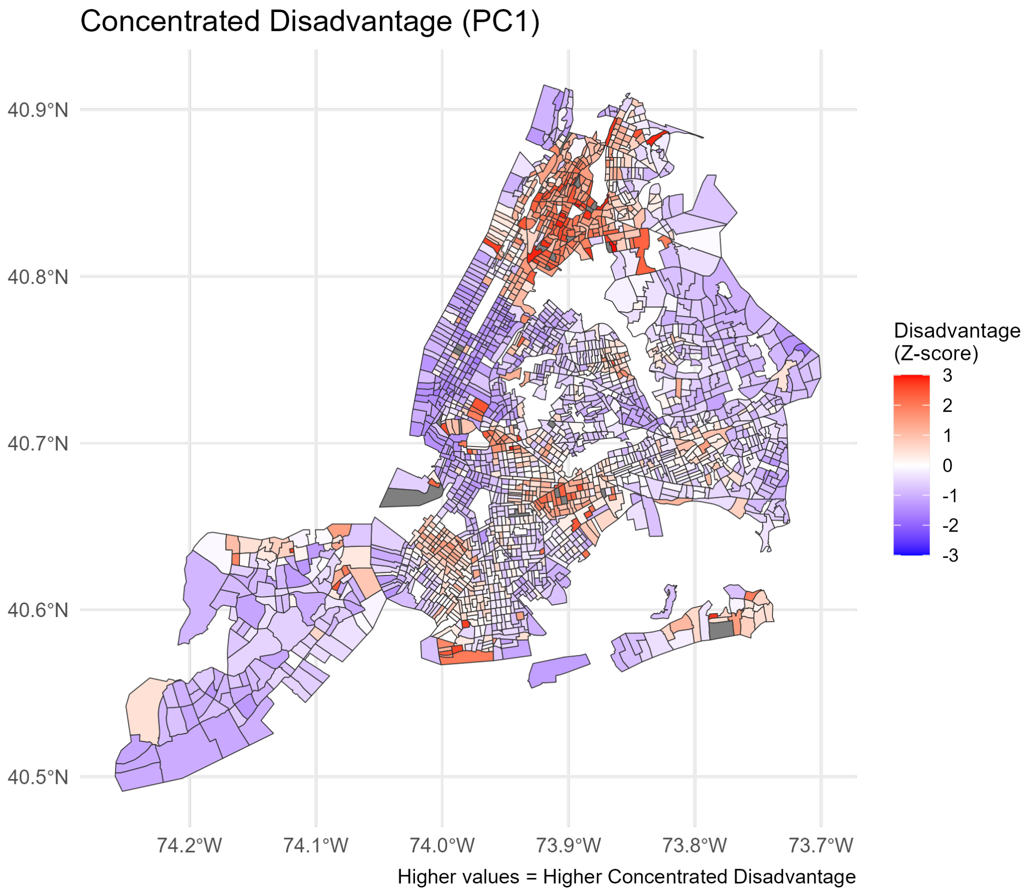


Figure 1

5.1.2 Residential Instability

The PCA for residential instability produced a PC1 that explained approximately 41% of the total variance (eigenvalue = 1.64; see Table 2). Recent residential mobility and housing vacancy loaded negatively, while foreign-born population and overcrowding loaded positively. This suggests that PC1 captures a continuum between neighbourhoods experiencing high turnover and disinvestment, and those characterised by high density and immigrant presence.

Table 2: Principal Component Loadings for Residential Instability

Indicator	**PC1 Loading**
% Moved in Past Year	−0.665
% Vacant Housing Units	−0.567
% Foreign-Born Population	0.682
% Overcrowded Households	0.639

In NYC, where nearly 38% of residents are foreign-born (U.S. Census Bureau, 2023), positive loadings on foreign-born concentration and overcrowding may reflect the stability of long-established immigrant communities rather than residential instability. As such, PC1 is best interpreted as a dimension of residential structure, rather than a pure measure of instability.

Figure 2 presents a choropleth map of PC1 scores for residential instability.

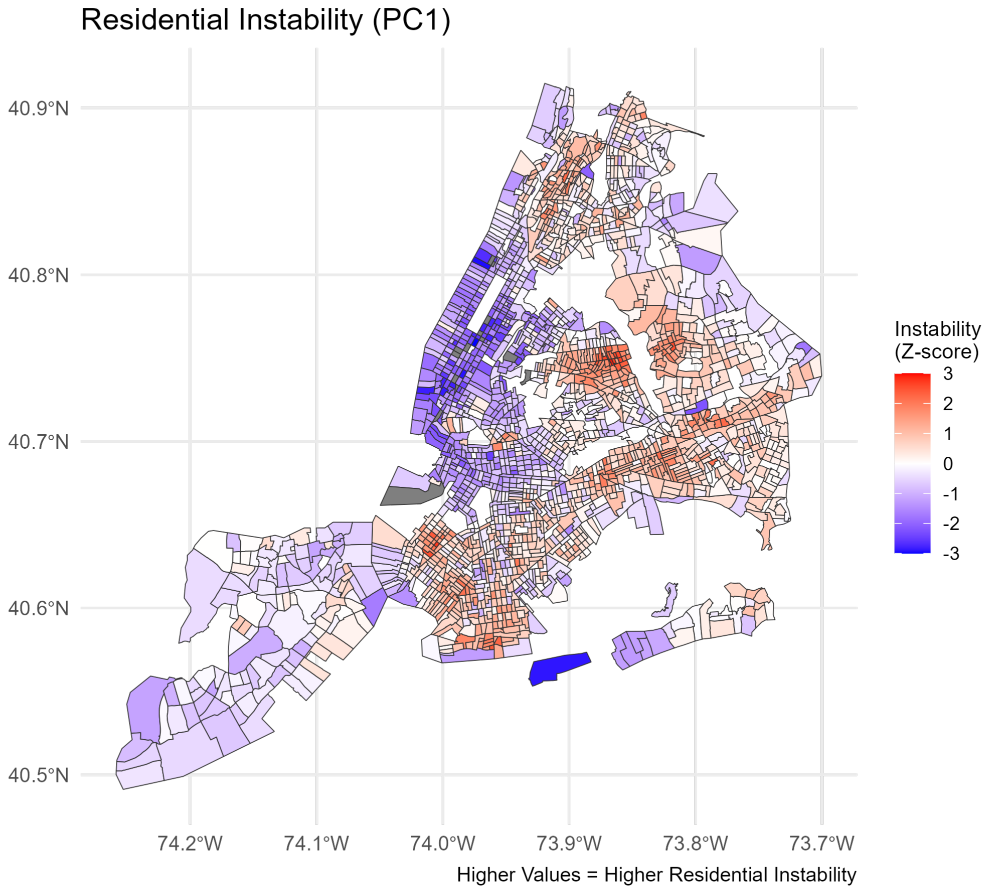
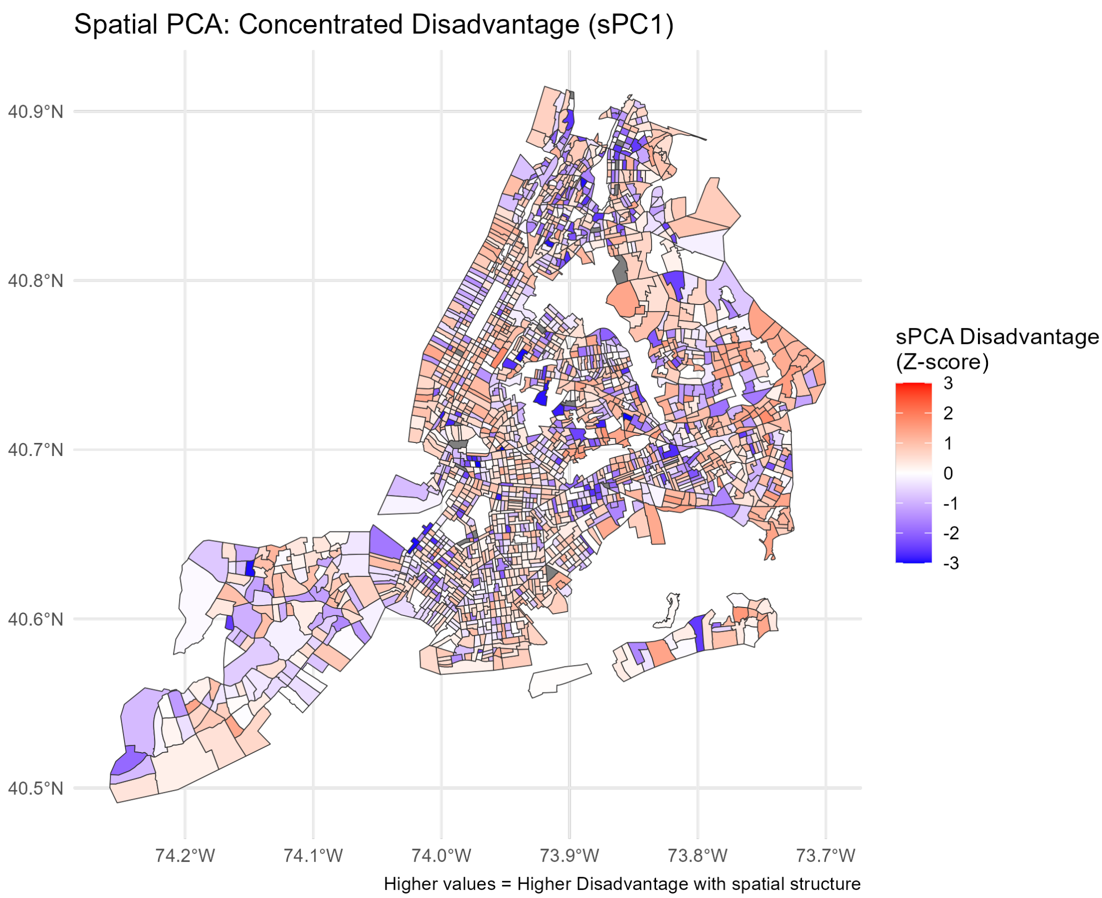


Figure 2

5.2 Spatial Principal Components Analysis (sPCA)

sPCA was used to assess whether the latent structural dimensions exhibited spatial patterning. For concentrated disadvantage, the first spatial component retained a similar loading structure to standard PCA and explained approximately 54% of the total variance (eigenvalue = 3.23, Moran's I = 0.56), indicating strong spatial clustering. For residential instability, the first spatial component explained 41% of the variance (eigenvalue = 1.64, Moran's I = 0.25) but showed weaker spatial dependence.

Full results are provided in Appendix Tables B1 and B2. Figure 3 and 4 presents choropleth maps of sPC1 scores for each construct.



Spatial PCA: Concentrated Disadvantage (sPC1)
40.9°N
40.8°N
40.7°N
40.6°N
40.5°N
74.2°W
74.1°W
74.0°W
73.9°W
73.8°W
73.7°W
sPCA Disadvantage
(Z-score)
3
2
1
0
-1
-2
-3
Higher values = Higher Disadvantage with spatial structure

Figure 3

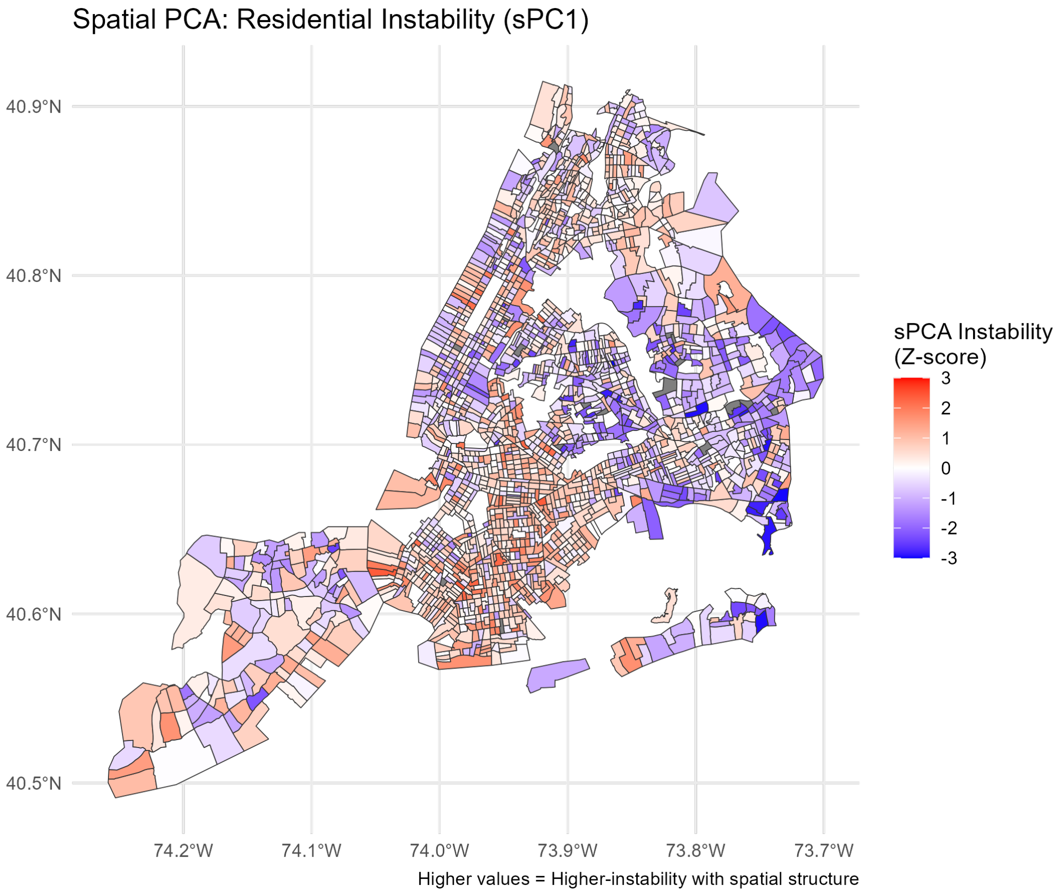


Figure 4

5.3 Negative Binomial Regression Models

5.3.1 Model with PCA Components

The PCA-based model (see Table 3) showed that concentrated disadvantage was strongly associated with shooting incidents ($\beta = 0.65$, $p < 0.001$), corresponding to a 91.5% increase in the expected shooting rate for each one standard deviation increase in the index. This supports Hypothesis 1, reinforcing theoretical expectations that entrenched socioeconomic hardship is a key driver of gun violence.

The residential instability component was negatively associated with shootings ($\beta = -0.11$, $p < 0.001$), implying lower rates of gun violence in tracts with higher PC1 scores. This finding does not support Hypothesis 2 and may reflect the conceptual ambiguity of the component.

Table 3: Negative Binomial Regression Results Using PCA Components

Variable	Estimate	Std. Error	z-value	p-value
Intercept	-7.922	0.059	-133.29	< 0.001
Concentrated Disadvantage (PCA)	0.643	0.023	27.71	< 0.001
Residential Instability (PCA)	-0.151	0.034	-4.40	< 0.001
% Black Residents	2.390	0.088	27.10	< 0.001
% Aged 15–29	-2.383	0.801	-2.98	0.003

Figure 5 maps the Pearson residuals from the PCA-based model, highlighting areas of model under- and over-prediction.

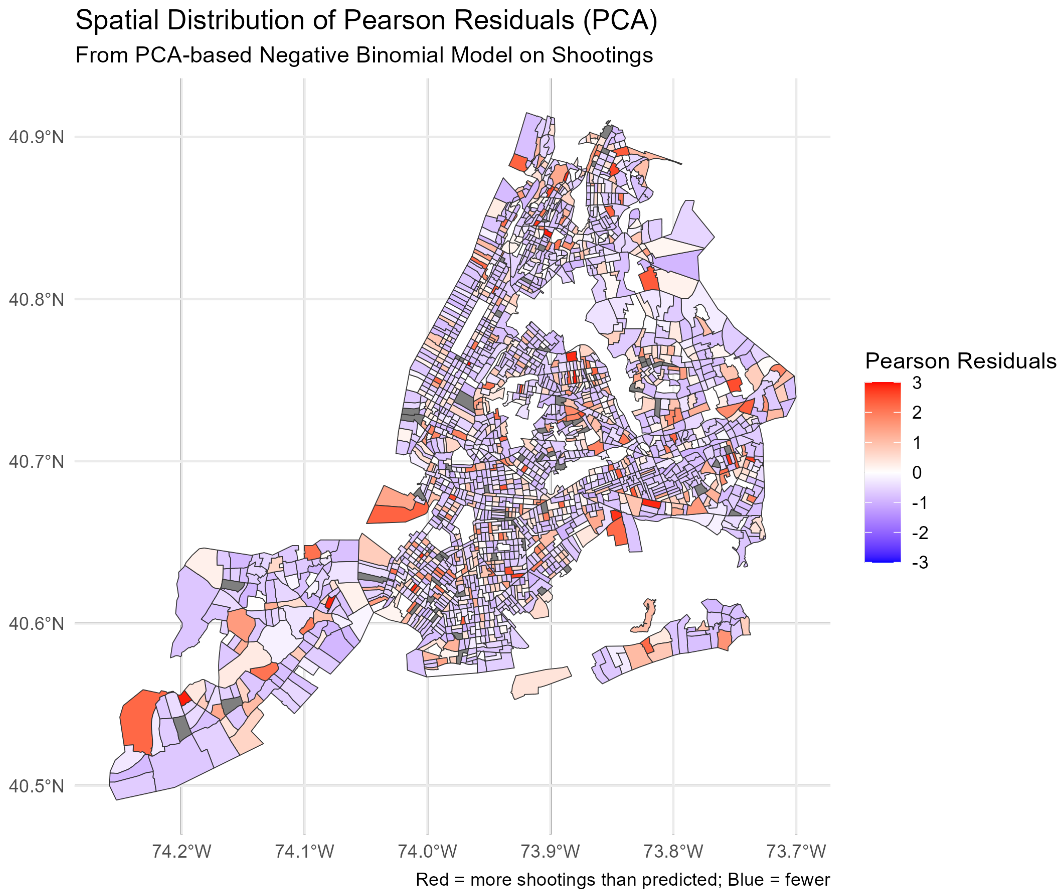


Figure 5

5.3.2 Model with sPCA Components

In contrast, the model using sPCA components (see Table 4) yielded weaker results. Disadvantage (sPCA) was negatively associated with shootings ($\beta = -0.08$, $p = 0.007$), while instability (sPCA) was not statistically significant. Although the sPCA model reduced spatial autocorrelation in residuals (Moran's $I = 0.008$, $p = 0.12$), overall model fit was worse (AIC = 9,220 vs. 8,774), and coefficients were either non-significant or contrary to theoretical expectations. These results do not support Hypothesis 3, which proposed that accounting for spatial autocorrelation in the predictors would improve model performance. This may reflect a trade-off between spatial smoothing and predictive accuracy in a spatially heterogeneous city like NYC.

Table 4: Negative Binomial Regression Results Using sPCA Components

Variable	Estimate	Std. Error	z-value	p-value
Intercept	-8.047	0.053	-151.55	< 0.001
Spatial Disadvantage (sPCA)	-0.131	0.036	-3.66	< 0.001
Spatial Instability (sPCA)	0.038	0.033	1.15	0.252
% Black Residents	3.150	0.082	38.25	< 0.001
% Aged 15–29	0.297	0.607	0.49	0.625

Figure 6 presents residuals from the sPCA-based model, illustrating reduced spatial clustering relative to the PCA model.

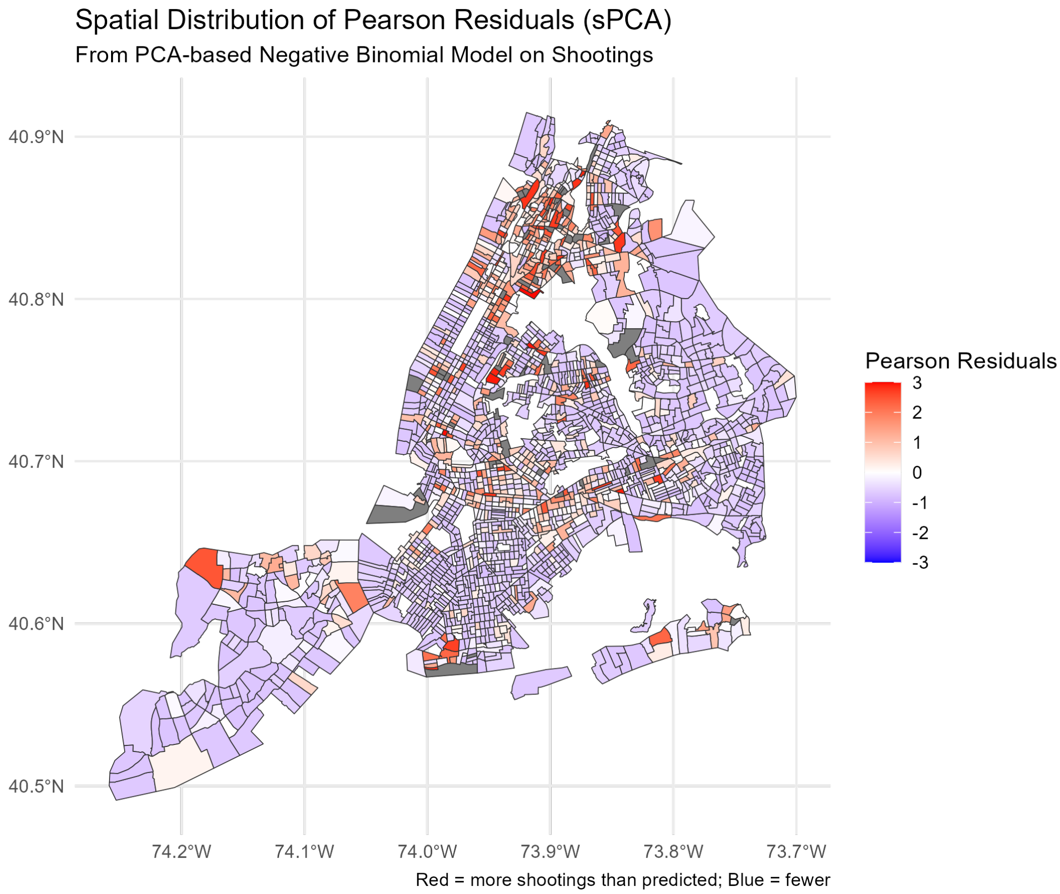


Figure 6

Spatial Distribution of Gun Violence

Figure 7 displays a choropleth map of shooting incidents per 1,000 residents across New York City census tracts, illustrating the spatial concentration of gun violence across the city.

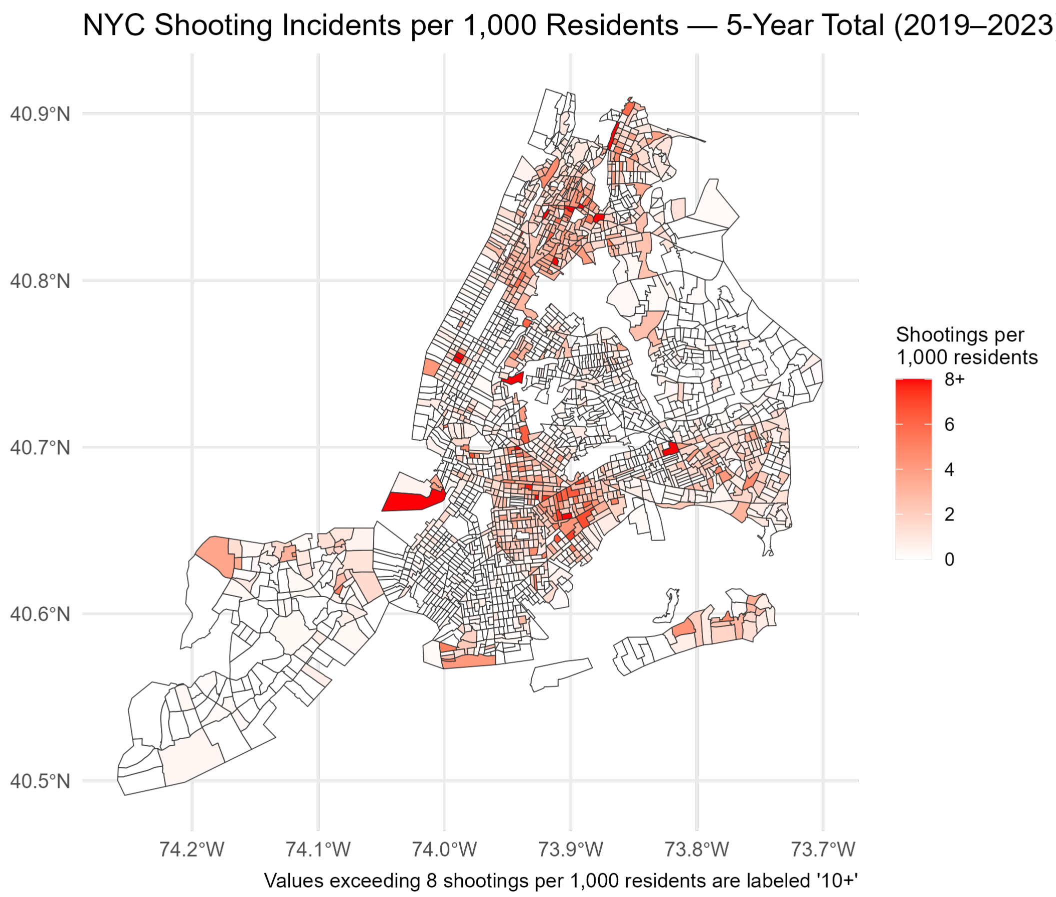


Figure 7

6 Discussion

This study examined how neighbourhood-level structural characteristics relate to the spatial distribution of shootings across NYC census tracts. Consistent with theoretical expectations, concentrated disadvantage emerged as a robust and significant predictor of gun violence, reinforcing prior research linking entrenched socioeconomic hardship to elevated levels of violence.

By contrast, residential instability was a weaker and less conceptually coherent predictor, with effects opposite to expectations. Although grounded in established theory, some indicators, particularly foreign-born population, may reflect stability in the context of long-standing immigrant communities, especially in a city as diverse as New York. This highlights the limitations of applying standard constructs uniformly across urban contexts. Future work should consider tailoring instability indices to better reflect urban demographic characteristics.

Spatial PCA was introduced as a robustness check to capture spatially structured latent dimensions. While the components demonstrated spatial clustering, including them in the model reduced overall fit and yielded weaker or counterintuitive associations. This likely reflects the fine-grained spatial heterogeneity of NYC, where adjacent tracts often differ sharply in social and economic composition. In such environments, spatial smoothing may obscure meaningful local variation.

Spatial autocorrelation in the original PCA model may reflect properties of the outcome variable itself, rather than omitted predictors. Patterns of violence often arise from dynamic processes, such as retaliatory violence, diffusion, or gang activity, that static structural indicators cannot fully capture. While this study used 5-year cumulative data, future research could build on this by incorporating longitudinal data, measures of local exposure to violence, or insights from neighbourhood-level social dynamics.

A Model Specification

$$\log(\mu_i) = \beta_0 + \beta_1 \text{Disadvantage}_i + \beta_2 \text{Instability}_i + \beta_3 \%\text{Black}_i + \beta_4 \%\text{Male15–29}_i + \log(\text{Population}_i) \quad (1)$$

Where:

- μ_i is the expected count of shooting incidents in census tract i.
- Disadvantage_i is the PCA or sPCA-derived index of concentrated disadvantage.
- Instability_i is the PCA or sPCA-derived index of residential instability.
- $\%\text{Black}_i$ is the proportion of residents identifying as Black or African American.
- $\%\text{Male15–29}_i$ is the proportion of males aged 15 to 29 in census tract i.
- $\log(\text{Population}_i)$ is the offset term adjusting for tract population size.

B Spatial Principal Component Loadings

Table B1: Spatial PCA Loadings for Concentrated Disadvantage (sPC1)

Indicator	**sPC1 Loading**
% Below Poverty Line	0.856
% Receiving SNAP	0.883
% Unemployed	0.623
% Female-Headed Households	0.741
% No High School Diploma	0.701
% Aged Under 18	0.568

Note: Eigenvalue = 3.23; Moran's I = 0.56.

Table B2: Spatial PCA Loadings for Residential Instability (sPC1)

Indicator	**sPC1 Loading**
% Moved in Last Year	−0.665
% Vacant Units	−0.567
% Foreign-Born	0.682
% Overcrowded Housing	0.639

Note: Eigenvalue = 1.64; Moran's I = 0.25.

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