NYPD Arrests Data Analysis

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Contents

Abstract

In the bustling metropolis of New York City, growing concerns about crime rates have prompted an in-depth exploration of the dynamic reasons behind it. Prior studies have provided fragmented insights, and they often focus on isolated factors or limited time scales. Our study seeks to fill these gaps by providing a comprehensive understanding of crime models in NYC. This study dives into the multifaceted nature of crime and examines specific variables including gender, age, race, area, and timing of incidents by combining visual graphs, interactive programs, and statistical modeling methods. Through the straight but highly efficient methodology, our goal is to bridge the gap between crime statistics and the general public in order to provide approachable and actionable insights for residents and policymakers. This research has important implications for urban planning, law enforcement strategies, and community engagement activities.

1 Introduction

With its large and diverse population, NYC is a global center of culture, commerce, and entertainment. However, like many large cities, New York faces the long-standing challenge of ensuring the safety of its residents and visitors. With growing concerns about the city's crime rate, people are increasingly seeking insights that can help them safely navigate their daily lives and reduce potential risks.

The primary objective of this study is to illustrate crime patterns and correlations using a large dataset of NYPD crime records. By focusing on variables such as gender, age, race, area, and time of incident, we aim to provide a comprehensive picture of crime dynamics in NYC. Through diverse charts, interactive programs, and advanced visualization tools, we hope to bridge the gap between complex data and comprehensibility for the general public. These insights can provide individuals with actionable information that helps them to make informed decisions in real-time.

This study has two broad significances. First, it provides citizens with a clear, data-driven view of the state of safety in NYC. It also has the potential to increase the perceived level of crime and allow residents to act with greater confidence and caution. Second, the patterns and relationships revealed in this research can provide valuable information to policymakers, such as the New York government and city safety agencies. By understanding the intricate network of factors that may influence crime rates, these agencies can design better prevention strategies, allocate resources more efficiently, and implement proactive measures. There are equally important indications for improving the ability of government departments to target and deploy crime more quickly under extreme social events, such as Covid-19.

Based on this basic research, future work may involve predictive analytics to forecast crime trends based on historical and current data. Digging deeper into the dataset may also reveal subtexts such as the impact of socioeconomic changes on crime during an epidemic or the role of urban infrastructure in safety. With our continuous refinement of our analytical framework, we hope to provide insights that will help NYC evolve into a safer and more resilient urban environment, thus ensuring the well-being of its diverse population.

1.1 Main Dataset

The main dataset we are using is the NYPD Arrests historic dataset. List of every arrest in NYC going back to 2006 through the end of the previous calendar year. This is a breakdown of every arrest affected in NYC by the NYPD going back to 2006 through the end of the previous calendar year. This data is manually extracted every quarter and reviewed by the Office of Management Analysis and Planning before being posted on the NYPD website. Each record represents an arrest affected in NYC by the NYPD and includes information about the type of crime, the location and time of enforcement. In addition, information related to suspect demographics is also included.

This dataset consists of 5488709 rows and 19 columns, the column variables are as follows:

Variable	Explanation
ARREST_KEY	Randomly generated persistent ID for each arrest
ARREST_DATE	Exact date of arrest for the reported event
PD_CD	Three digit internal classification code
PD_DESC	Description of internal classification corresponding with PD code
KY_CD	Three digit internal classification code
OFNS_DESC	Description of internal classification corresponding with KY code
LAW_CODE	Law code charges
LAW_CAT_CD	Level of offense
ARREST_BORO	Borough of arrest
ARREST_PRECINCT	Precinct where the arrest occurred
JURISDICTION_CODE	Jurisdiction responsible for arrest
AGE_GROUP	Perpetrator's age within a category
PERP_SEX	Perpetrator's sex description
PERP_RACE	Perpetrator's race description
X_COORD_CD	Midblock X-coordinate for New York State Plane Coordinate System
Y_COORD_CD	Midblock Y-coordinate for New York State Plane Coordinate System
Latitude	Latitude coordinate for Global Coordinate System
Longitude	Longitude coordinate for Global Coordinate System
Lon_Lat	Georeferenced Point Column based on Longitude and Latitude fields

Table 1: Data Variables Summary

1.2 Secondary Dataset

It's natural to consider some influential factors on the number of arrests. One of such major factors can be the unemployment rate. We found a dataset of the monthly unemployment rate in NY.

This dataset comes from the Current Population Survey (CPS), also known as the household survey.

Civilian Labor Force includes all persons in the civilian noninstitutional population ages 16 and older classified as either employed or unemployed.

Unemployed persons are all persons who had no employment during the reference week, were available for work, except for temporary illness, and had made specific efforts to find employment some time during the 4 week-period ending with the reference week. Persons who were waiting to be recalled to a job from which they had been laid off need not have been looking for work to be classified as unemployed. The unemployment rate is the unemployed percent of the civilian labor force: $100 * \frac{unemployed}{civilianlaborforce}$.

This dataset contains 404 rows (monthly unemployment rate) and 2 columns (monthly date and unemployment rate). To align with the main dataset, we choose to use the years from 2006 to 2022 of this dataset to analyze.

2 Methodology

In this report, we will utilize stacked bar plot to see relations among arrests, race, and age groups; we will use population pyramid to see the relations among arrests, borough districts of NYC, and gender; we will also use line plots to show the overall trends of arrest counts aligned with unemployment rate, which might be a cause of crimes.

Based on the information provided by these plots, we will then try to construct a time-series Autoregressive Integrated Moving Average (ARIMA) Model, and perform a linear regression model of arrests vs unemployment rate, using a merged dataset of the main and the secondary. We will see if we can use these models to somewhat capture the pattern of arrests and predict future crimes.

As the Covid-19 pandemic seems to have a considerable impact on the number of arrests, we will then dig deeper into the Covid-19 time period to perform some specific analysis. Using the seasonal plot can help us see which years have abnormal changes in the crime rate from 2018 to 2022. Then we will analyze changes in some major crime types we believe will be most affected by Covid-19 based on the seasonal plot. Using heatmap to see those crime types' changes between 2018 and 2022, and to see in which year they are most concentrated. We know from the heatmap the growth of the major crime categories. The use of a dumbbell plot can intuitively show us the crime volume of these major crime categories in 2019 and 2020 when the Covid-19 outbreak occurred. In other words, we can see how much it increased during the year of the outbreak. Based on this analysis from 2019 to 2020, we will use the treemap to show what each specific category includes. From this diagram, we can see which subdivision has the most crime types and has the most crime volume.

At last, we will discuss our findings and make some advice to help with controlling and preventing future crimes.

3 Results

3.1 Overview

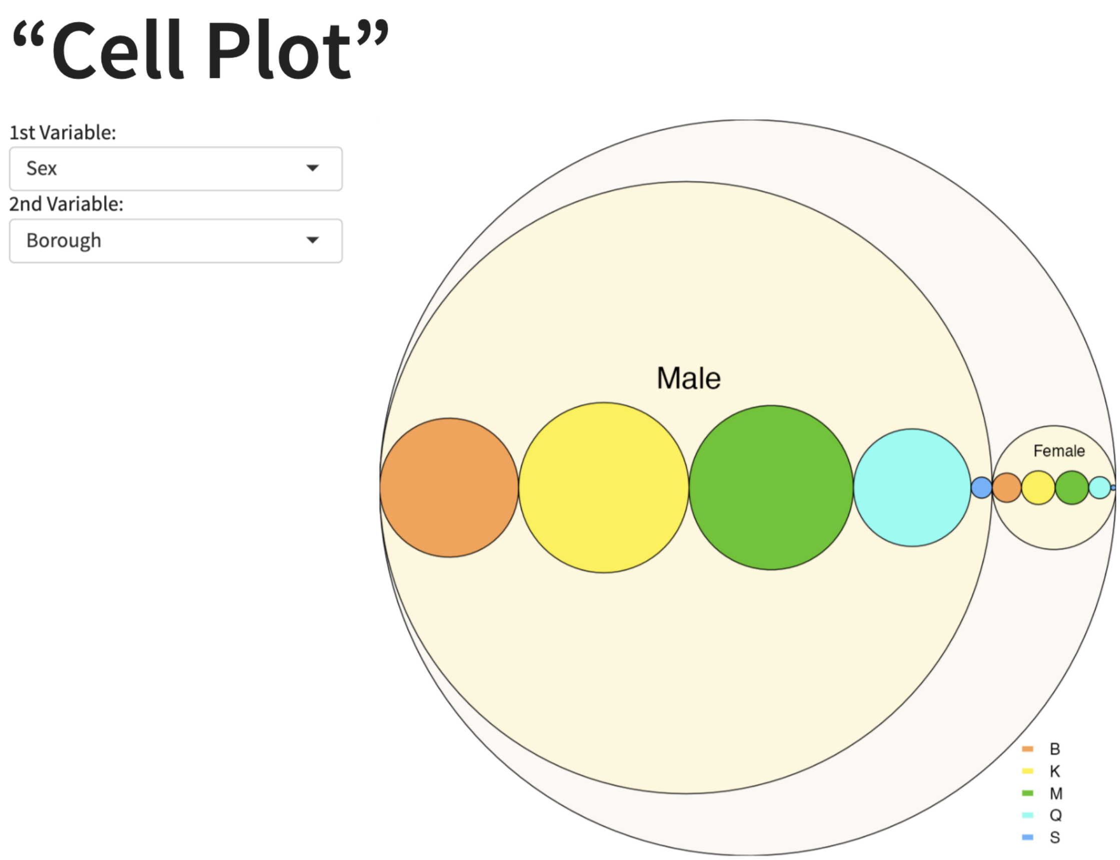

Figure 1: Killer Plot

Our "Cell Plot" utilizes proportional circle sizes to represent the relative comparison across different variables. In this graph, for instance, two primary variables are considered: 'Sex' and 'Borough'. The circles are categorized by sex, 'Male' and 'Female', and are color-coded according to five boroughs (B, K, M, Q, S), each denoted by a distinct color. The size of each circle corresponds to the quantity or proportion of the data it represents. Larger circles indicating higher values. In this instance, the circles under 'Male' are significantly larger than those under 'Female', suggesting a larger count or a higher proportion of a certain characteristic or demographic within male categories across all crimes in NYC. In the two circles representing the number of male and female offenders, we can also observe that the circles representing the three districts B, K, and M are the largest, which indicates that these three districts are the high crime areas in both the male and female gender systems.

With this intuitive visual method, we can immediately and visually grasp the distribution and magnitude of different categories of data without having to use a numerical scale. However, for a more granular analysis, we examine a "stacked bar plot" in the next step, which includes a numerical scale. This would enable a detailed dissection of the exact figures and proportions, providing a quantitative grounding to the qualitative insights gained from the "Cell Plot". This chart will complement the "Cell Plot" by providing specific values that may affect the interpretation of the data and the subsequent decision-making process.

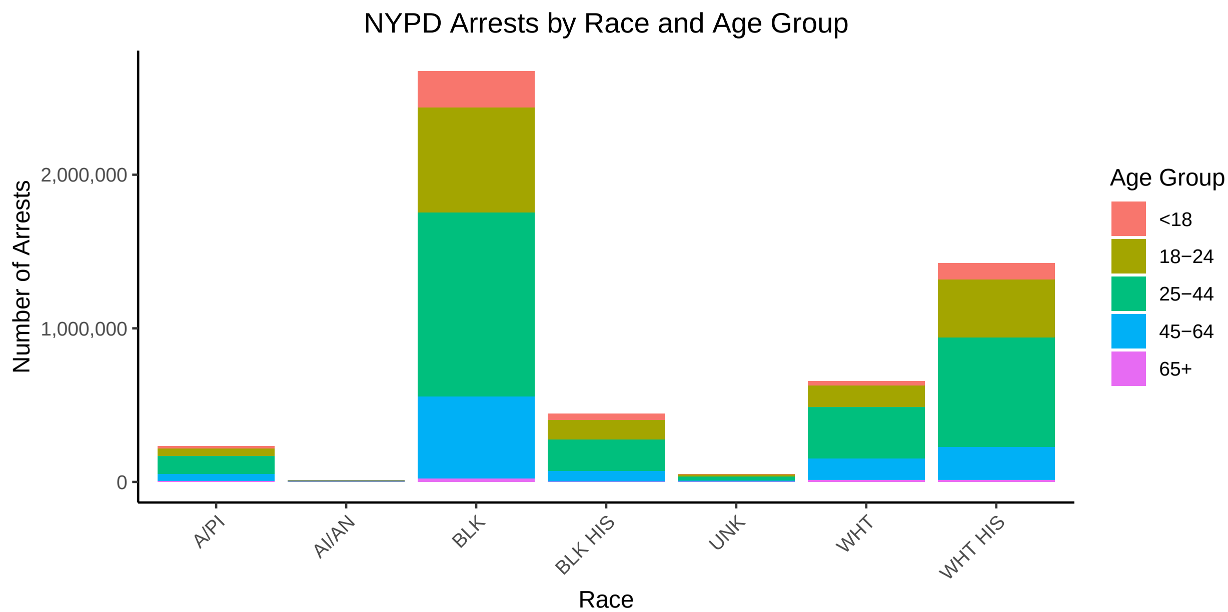

Figure 2: Stacked Barplot of Arrests by Race and Age Group

Abbreviation	Full Term
AI/AN	AMERICAN INDIAN/ALASKAN NATIVE
A/PI	ASIAN / PACIFIC ISLANDER
BLK	BLACK
BLK HIS	BLACK HISPANIC
UNK	UNKNOWN
WHT	WHITE
WHT HIS	WHITE HISPANIC

Table 2: Race Abbr. Description

The stacked bar plot analyzes the relationship between race, age, and crime rates in NYPD arrest data. Each bar represents a race, with colors indicating age groups: pink for minors under 18, brown-green for youths 18-24, green for middle-aged 25-44, blue for older adults 45-64, and purple for those 65 and older. The data reveals variations in arrest numbers across races and age groups. Blacks have the highest number of arrests, followed by White Hispanics, Whites, and Black Hispanics. A consistent trend across all races is that the most arrests occur among individuals aged 25-44 (green), followed by those aged 18-24 (brown-green). This trend suggests that economic, social pressures, and psychological factors might influence criminal behavior in these age groups.

This analysis highlights the need for law enforcement in New York to focus on young and middle-aged adults. Additionally, it underscores the importance of considering the mental and emotional well-being of these specific age groups. This data can inform strategies for equitable law enforcement across different populations and races and assist the government in tailoring crime prevention measures for various districts, including police deployment and safety education.

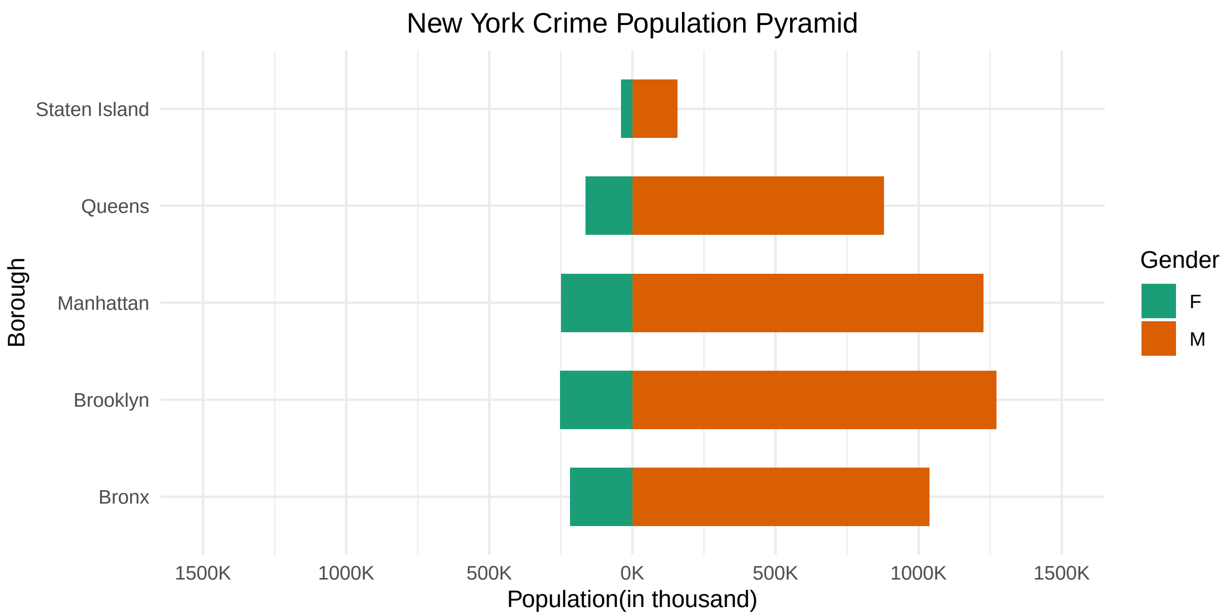

Figure 3: Population Pyramid of Arrests by Borough and Gender

The "New York Crime Population Pyramid" chart displays the gender distribution of criminals across NYC boroughs using a two-color scheme: green bars for females and yellow bars for males. The x-axis represents boroughs, and the y-axis shows the crime population in thousands.

The chart reveals a significant gender disparity in crime, with a notably higher number of male criminals, especially in the Bronx and Brooklyn. The ranking of boroughs by crime cases is Staten, Queens, Bronx, Manhattan, and Brooklyn, with Brooklyn having the highest rate, possibly influenced by its large population and specific post-pandemic challenges like recession and unemployment.

This pyramid chart serves as a basis for further socioeconomic and policy analysis, highlighting the need for borough-specific strategies. It underlines the importance of considering gender differences in crime rates and the socio-economic and educational factors contributing to these disparities.

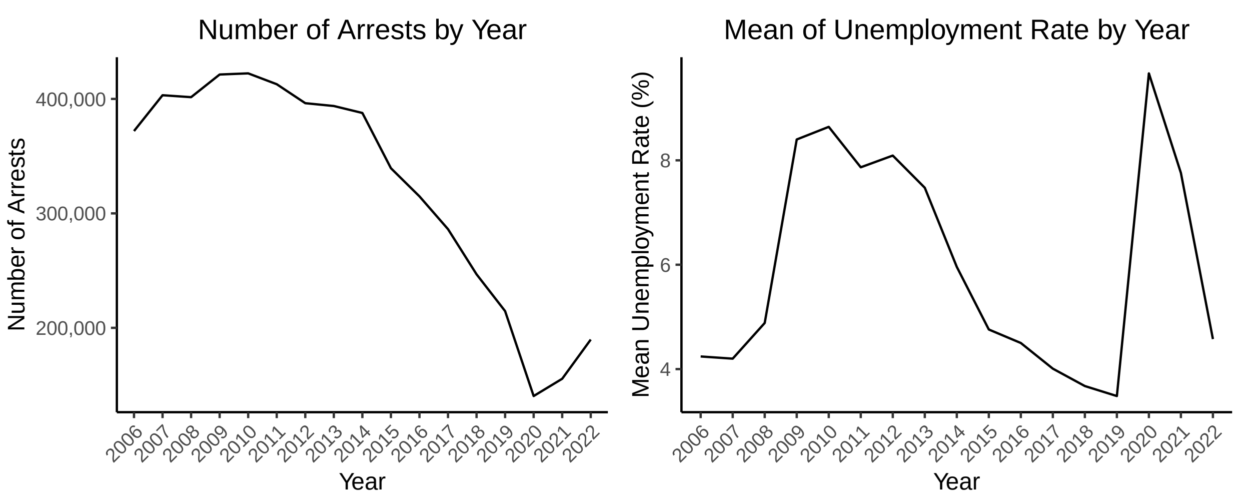

Figure 4: Line Plots of Arrests and Mean Unemployment Rate by Year

The line plot shows NYPD arrest trends, peaking in 2010, declining until 2020, and then rising sharply post-Covid-19. This pattern suggests the potential for a time-series model. A parallel trend is observed with unemployment rates, which also peaked in 2010 and increased rapidly after the pandemic. The similarity in trends between arrests and unemployment rates indicates a possible correlation, warranting a merged dataset analysis and linear regression to explore the relationship between these two factors.

3.2 Statistical Modeling

3.2.1 Time-Series Autoregressive Integrated Moving Average Model

Since this dataset has the specific dates of each arrest, we can probably perform a time-series model in this case. As the fluctuation of arrest counts from day to day is huge, we choose to perform the model with respect to monthly total. The model we are trying to use is the Autoregressive Integrated Moving Average Model.

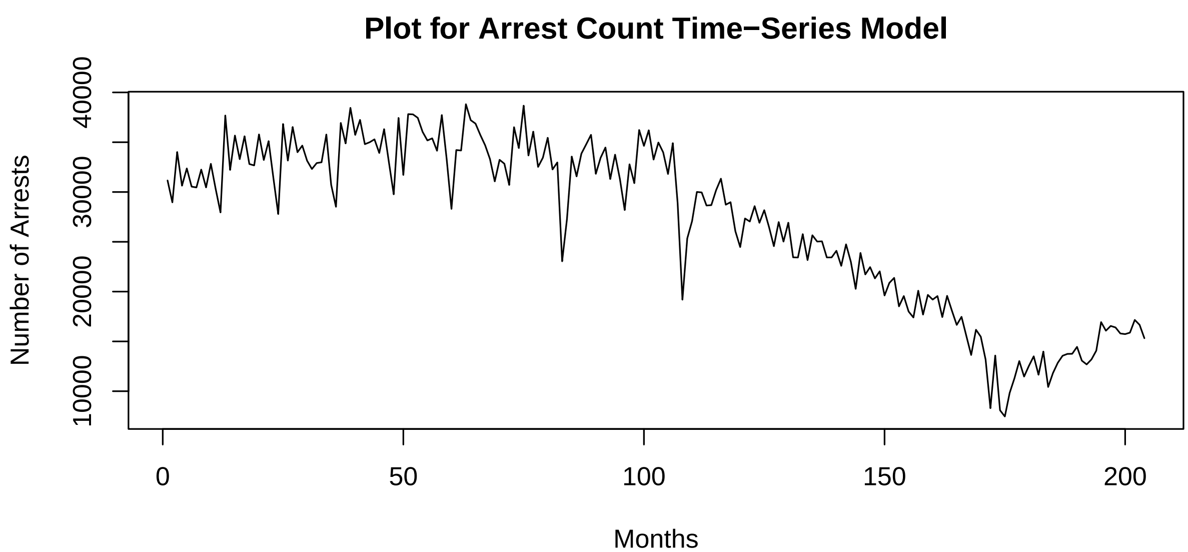

Figure 5: Plot for Time-Series Model

Based on the plot of our time-series model, we can see that the overall trend follows the line plot before. There is a tiny decreasing trend from the year 2006, and drops more steeply after about 100 to 110 months (which was around 8 to 9 years later than 2006). Then at about 175 months, the arrest count rises steeply again. This time period was around 2020 to 2021. This might be the effect of the Covid-19 pandemic that harshly impacted the general economic environment. People during that period became more anxious and were easier to go rogue under huge pressure of daily life.

According to the ARIMA model's numeric summary above, however, this model does not seem to capture the real trend well. Since the log-likelihood value is -1880.55, which is too low, and AIC is 3765.1, BIC is 3771.73, which is too large, this time-series ARIMA model does not fit the data well. This might be the effects of the huge fluctuations. Thus, we will need to investigate further using different models.

Statistic	Value
log-likelihood	-1880.55
AIC	3765.1
BIC	3771.73

Table 3: ARIMA Model Summary

According to the ARIMA model's numeric summary above, however, this model does not seem to capture the real trend well. Since the log-likelihood value is -1880.55, which is too low, and AIC is 3765.1, BIC is 3771.73, which are too large, this time-series ARIMA model does not fit the data well. This might be the effects of the huge fluctuations. Thus, we will need to investigate further using different models.

3.2.2 Linear Regression Model with Unemployment Rate

Now, we are trying to perform a linear regression of arrests versus unemployment rate.

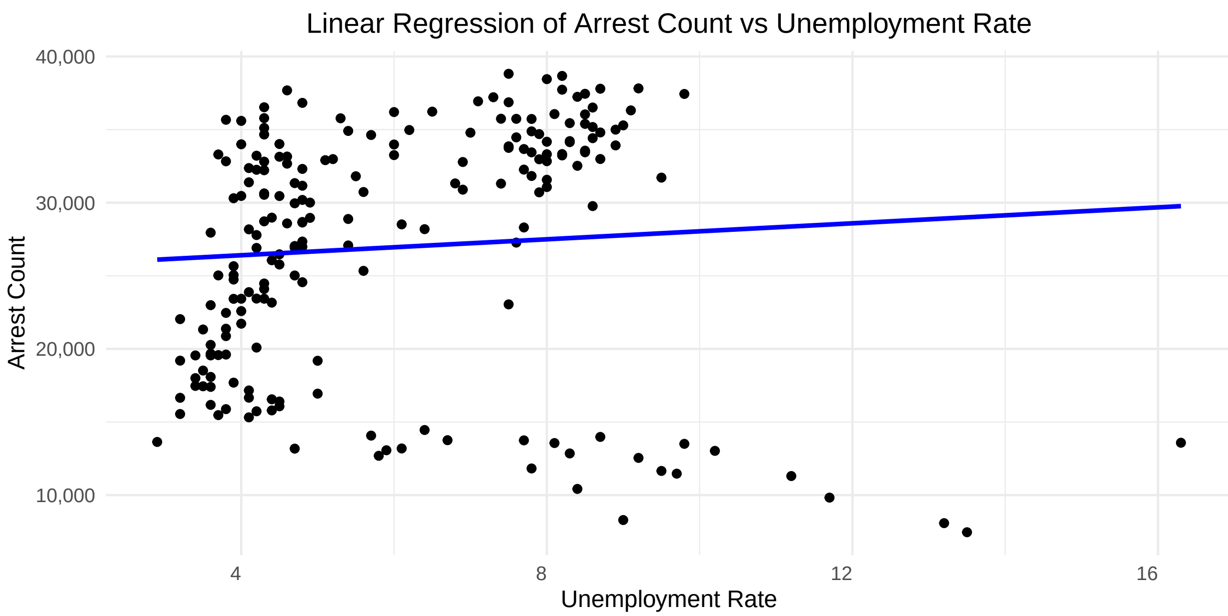

Figure 6: Plot for Linear Regression Model of Arrest Count vs Unemployment Rate

The linear regression plot above does not seem to be a good fit for the data, as the blue line of best fit does not capture the pattern of the data points. We can see there are some data points lying at the bottom of this plot holding the line down. Compared with Fig. 3, we can speculate that these data points might be the period after 2020 when unemployment rates rose severely, while the number of arrests started to increase but not to another peak as the unemployment rate did. There seems to be a weak linear trend if we exclude these potential influential points.

According to the numeric summary of this linear regression model above, since the p-value is 0.2898 which is greater than 0.05, we can say that we do not have significant evidence to reject the null hypothesis of the coefficient to be 0. Thus, this first version of linear regression does not fit well to the merged dataset of arrests versus unemployment rate. However, we do see there are correlations between arrests and unemployment rate. We need to do a diagnostic to optimize the linear regression model to further investigate.

As we saw there might be strong effects around the Covid-19 pandemic. We would like to dig deeper into this time period.

Statistic	Value
Intercept	25313.4
Coefficient of Unemployment Rate	273.0
p-value	0.2898

Table 4: Linear Regression Model Summary

According to the numeric summary of this linear regression model above, since the p-value is 0.2898 which is greater than 0.05, we can say that we do not have significant evidence to reject the null hypothesis of the coefficient to be 0. Thus, this first version of linear regression does not fit well to the merged dataset of arrests versus unemployment rate. However, we do see there are correlations between arrests and unemployment rate. We need to do diagnostic to optimize the linear regression model to further investigate.

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3.3 Specific Analysis around Covid-19 Pandemic

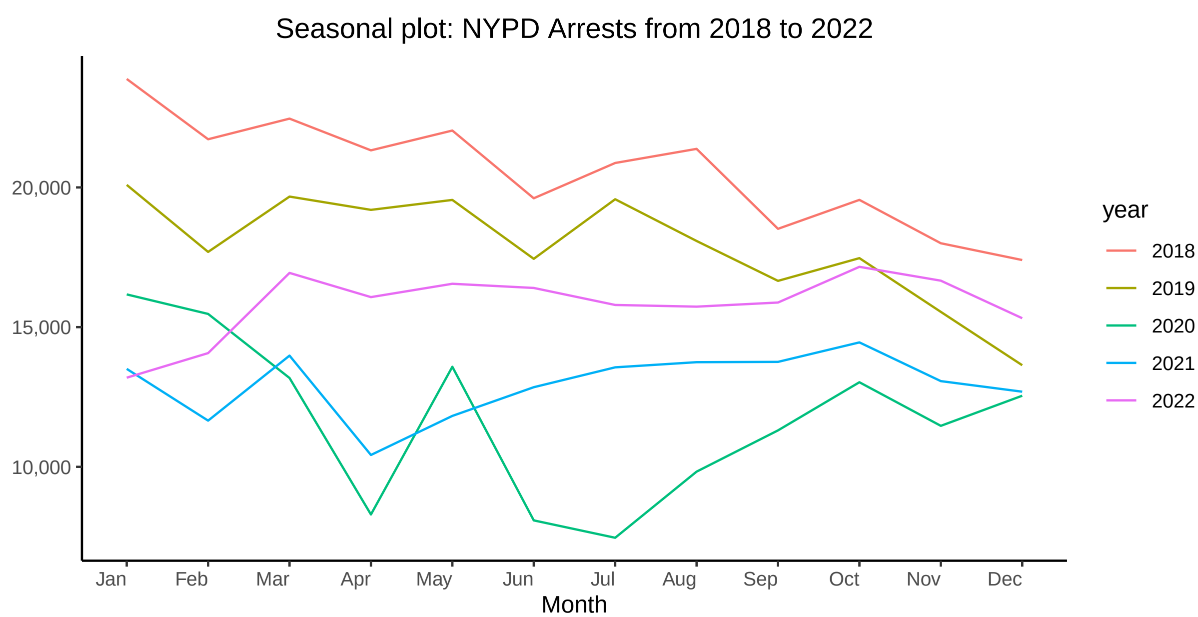

Figure 7: Seasonal Plot of Arrests from 2018 to 2022

This seasonal plot illustrates New York City's crime trends from 2018 to 2022, including the Covid-19 pandemic period. It helps the NYPD to allocate resources effectively across boroughs. The x-axis shows months, and the y-axis shows monthly crime numbers. There was a usual decline in crime from January in 2018 and 2019, with January having the highest rates. However, 2020 saw a notable decrease in crimes during the first four months, likely due to the pandemic reducing public gatherings.

Yet, this drop was short-lived. As NYC faced recession and social security cuts, crime rates surged around May 2020, doubling to about 13,000 offenses per month. Restricted public spaces and protests during the pandemic may have influenced these rates. With stabilizing pandemic conditions and stricter regulations, crime rates dipped in June but rose sharply in July due to economic and psychological pressures. From 2020, crime rates showed an overall increasing trend. This graph provides insights into how holidays, events, and broader socio-economic factors like the economy, social isolation, and law enforcement practices influenced crime rates during this period.

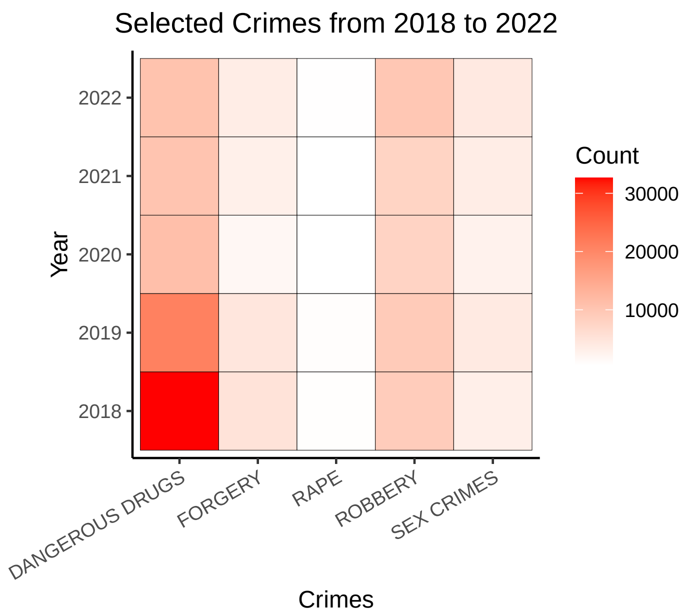

Figure 8: Heat Map of Selected Crimes from 2018 to 2022

In this heatmap, we have analyzed five types of crimes that occurred in New York between 2018 and 2022. This visual tool employs a color gradient to indicate varying levels of crime incidence, offering a clear, at-a-glance understanding of the data. The x-axis classifies the crimes into five categories: Dangerous Drugs, Forgery, Rape, Robbery, and Sex Crimes, while the y-axis spans the years from 2018 to 2022. Different shades in the heatmap correspond to the frequency of each crime type. These five crime categories were selected due to notable rate fluctuations during the Covid-19 pandemic, as previously identified in seasonal graphs. We aim to explore the causes behind these shifts. Crime rate changes can stem from various factors, particularly during an extraordinary period like the Covid-19 crisis. Hence, our focus is on the five most prevalent crime types reported by the NYPD, which are likely impacted by the pandemic.

The heatmap reveals that robbery and drug-related offenses are the most frequent crimes across all years, significantly surpassing forgery, rape, and sex crimes. The incidents related to dangerous drugs show a marked decrease after 2020, coinciding with the start of the global pandemic, suggesting that containment policies might have impeded drug trafficking and use. These data imply that the embargo strategies during the pandemic could have curtailed drug-related crimes by limiting public gatherings and people's mobility, potentially disrupting drug trafficking routes. Additionally, the stringent enforcement of lockdowns might have heightened surveillance in public areas, traditionally hotspots for drug sales.

Robbery persists with higher frequency than drug offenses and remains consistent throughout the analyzed period. This suggests that robbery is deeply embedded in NYC's social fabric, possibly exacerbated by the widespread economic hardship and health crises during this time. Conversely, despite the socio-economic turmoil in 2020 — rising unemployment, recession, and widespread social unrest — there was no notable surge in crimes like robbery, prompting further investigation to inform future crime prevention efforts.

This heatmap does more than visualize crime rates; it reflects the community's reaction to external stressors like Covid-19. While some measures may have unintentionally reduced drug-related offenses, the persistence of crimes such as robbery underscores the necessity for focused interventions. Our analysis concludes that policymakers need to devise comprehensive, sustained strategies to address deep-seated crime, ensuring the ongoing safety of New York's residents.

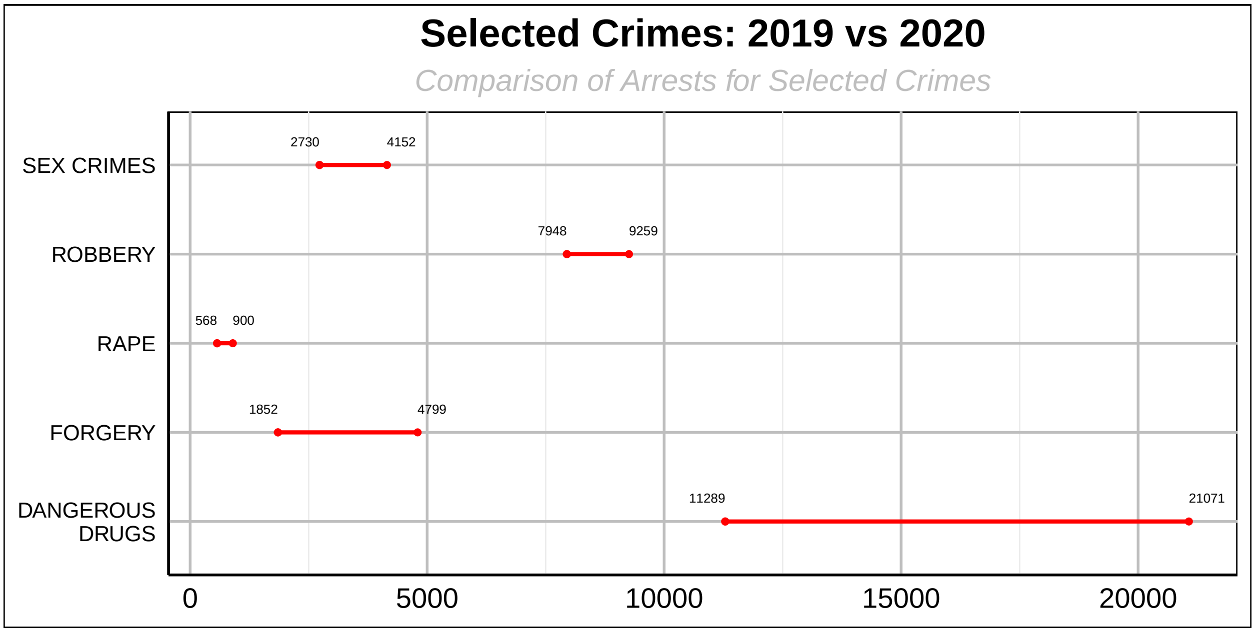

Figure 9: Dumbbell Chart of Selected Crimes of 2019 vs 2020

The image above depicts a dumbbell chart, an effective tool for visualizing the relative positions between two points in time, such as growth and decline, and for comparing distances between two categories (Prabhakaran). Due to the vast amount of criminal arrest data from the NYPD spanning from 2006 to 2020, a wide variety of offenses are analyzed. We chose to start our dumbbell chart in 2019—a year before Covid-19 had a significant impact—to highlight typical crimes in the first year the pandemic affected them. This period aligns with the specific change in crime rates that coincided with the outbreak of Covid-19, as noted in the Seasonal Plot.

Firstly, we focused on rape and sexual offenses, recognizing that the pandemic's enforced isolation could inadvertently increase domestic violence. The prolonged separation from family and roommates may escalate domestic sex crimes. The charts from 2019 to 2020 show a modest uptick in sex offenses, from 2,730 to 4,152, and rapes, from 568 to 900. We attribute this increase to Covid-19, theorizing that extended lockdowns may have heightened crimes due to unmet basic physical needs.

Secondly, the dumbbell chart illustrates a dramatic spike in arrests for dangerous narcotics between 2019 and 2020, with numbers exceeding 20,000 individuals. This surge could be linked to increased drug usage driven by the pandemic's resulting recession, unemployment, and stress. Supply chain disruptions from embargoes may have led to drug scarcity or price hikes, influencing drug-related crimes. Arrests for dangerous substances jumped from 11,289 to 21,071.

Moreover, with Covid-19 prompting the closure or limited operation of public spaces like malls, we anticipate a significant rise in fraud crimes between 2019 and 2020. The shift to online transactions heightens the risk of fraud and forgery, which our data reflects with forgery crimes increasing from 1,852 in 2019 to 4,799 in 2020.

Finally, the pandemic is likely to have spurred an uptick in robberies, as the data from 2019 to 2020 indicates an increase in robbery offenses from 7,948 to 9,259. The prevalence of store and street robberies during this time suggests a link to Covid-19 restrictions.

In summary, the dumbbell chart provides a clear depiction of the growth in different crime types, with certain categories, like dangerous drugs, recording offense numbers soaring beyond 20,000 annually. This prompts us to question whether the NYPD's arrest data can be disaggregated by specific types of drug offenses, warranting further analysis to seek solutions.

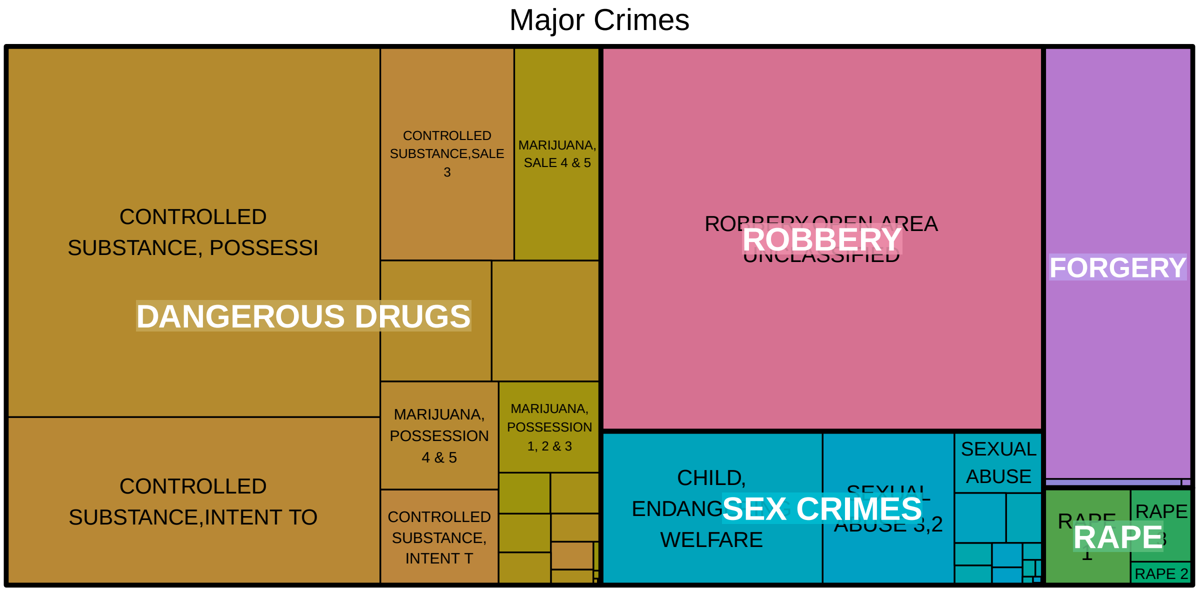

Figure 10: Treemap of Major Crimes

The image above, a Treemap, is a "great way to display hierarchical data through nested rectangles. `treemapify` package provides the necessary functions to convert the data to the desired format and to plot the actual graph." (Prabhakaran) In this graph, we illustrate the distribution of crime data wanted by the NYPD from 2019 to 2020, a period when New York faced the challenges posed by Covid-19. Among the five crime types we focus on—SEX CRIMES, RAPE, DANGEROUS DRUGS, FORGERY, and ROBBERY—it's clear that Dangerous Drugs leads in arrest types and has the highest number of criminal records. Following that, robbery ranks as the second most frequent offense, signaling a distressing sign of public order breakdown. The incidence of crimes in the Forgery and Sex Crimes categories appears similar. Out of the five crime categories reflecting the impact of the Covid-19 epidemic, Rape has the least occurrence.

Additionally, the Treemap enables us to identify the most prevalent offenses within each category. For instance, "Controlled Substance" and "PossessI" top the Dangerous Drugs category, indicating the illegal possession and distribution of these substances. The surge in demand for illicit drugs, driven by the pressures of Covid-19, has led to an uptick in related criminal activities. Thus, the NYPD should intensify control and surveillance efforts over these substances.

In the Forgery category, the most frequent offense is 'Forgery, Etc., Unclassified-Felo,' denoting a wide array of major, unclassified forgery offenses, possibly involving fraudulent documents or identities. Such criminal activities surged during the pandemic, likely due to diminished regulation. The subdivision 'Rape 1' records the highest number of crimes within the Rape category, representing a grave concern that necessitates further analysis to pinpoint causes and prevent further incidents. For Robbery, 'Robbery, Open Area Unclassified' emerges as the most prevalent, reflecting the typical nature of these crimes. In Sex Crimes, the most common classification between 2019 and 2020 is 'Child, Endangering Welfare.' This alarming data points to a threat to child safety and underscores the need for community collaboration with the NYPD to enhance protective measures.

In conclusion, the Treemap reveals the profound impact of various crimes on the economy, society, and individual safety during the Covid-19 pandemic. The NYPD and government authorities must devise strategic prevention and control measures for times of heightened risk to safeguard citizens' lives and property.

4 Conclusion

This analysis utilizes NYPD arrest records and unemployment data to provide an in-depth examination of crime trends in New York City, offering vital insights and recommendations for policymakers. The study reveals significant variances in crime rates when viewed through geographic and demographic lenses. Notably, there is a higher propensity for criminal involvement among males, particularly in Brooklyn and the Bronx. The age demographics showing the highest crime rates are those between 18-24 and 25-44 years old. The relationship between crime rates and socioeconomic factors, such as unemployment, is highlighted, underscoring the need for detailed analysis of this complex interplay. The Covid-19 pandemic has further complicated this landscape. The analysis shows a decline in drug-related crimes, likely attributable to movement restrictions, but an increase in crimes like robbery and counterfeiting, possibly driven by economic difficulties and opportunistic behaviors linked to the pandemic.

Based on these findings, the study suggests a three-pronged approach for improvement. First, there is a need for targeted crime prevention strategies, tailored to the unique needs of different boroughs and demographic groups. This involves not only intensified law enforcement in areas with higher crime rates but also community-centric initiatives to mitigate vulnerabilities. Second, the potential of predictive analytics in crime trend forecasting is evident. Future research should focus on refining these predictive models, incorporating factors such as socioeconomic shifts and urban infrastructure developments, to effectively anticipate and mitigate crime.

In conclusion, this study not only underscores the complexity of New York City's crime situation but also establishes a foundation for continued research and policy development. The insights gained are crucial for informed decision-making and efficient allocation of resources, ultimately contributing to the prevention of crime and the enhancement of public safety in New York City.

5 Discussion

Through our analysis, we can draw the following conclusions:

1. Diversity and complexity of crime: Our analysis highlights the diversity and complexity of crime in New York City. We observed that different crimes are affected by a variety of factors, including economic conditions, social unrest, unemployment levels and major social events, in particular the Covid-19 pandemic.

2. Impact of the epidemic: The pandemic has had a clear impact on various types of crime. Notably, crimes such as counterfeiting and sexual offenses have increased, while drug-related crimes have declined. This pattern reflects the direct and lasting impact of major social unrest on crime rates.

3. Unemployment and crime: There is a clear correlation between rising unemployment and increases in certain crimes. Economic challenges and unemployment often drive individuals to engage in criminal activity as a means of survival.

After 2022, the NYC government has always attached great importance to public safety and has adopted a series of measures to target various crimes, especially after specific social events (such as the Covid-19 epidemic). The following are some studies and measures that the NYC government has adopted and implemented for the following five major crime types:

For drug-related crimes, the NYPD has intensified operations against major drug trade routes and hotspots, while the government is conducting a public education campaign about the dangers of substance abuse and support resources. To combat robbery, police patrols have increased in high-risk areas, particularly post-pandemic, and community-based workshops are being held to educate citizens on robbery prevention and self-protection. For sex crimes, the government offers resources like anonymous hotlines and counseling services, alongside a public campaign to raise awareness about sexual crimes and consent. In tackling forgery, efforts are focused on enhancing online security through digital security training for citizens and stronger collaboration with financial institutions to fight counterfeiting and fraud. Regarding rape, rape crisis centers provide victims with legal, counseling, and medical support, and educational programs are conducted in schools and communities to teach consent and self-protection strategies.

In addition, New York City government is strengthening community-police partnerships to encourage crime reporting. After the epidemic, there is also an emphasis on providing financial assistance and vocational training to the unemployed to reduce economic pressure that may lead to crime.

To mitigate rising crime rates, our prevention strategies for major crimes like drugs, robbery, sex crimes, forgery, and rape include enhancing urban safety through technology, such as creating public safety zones and better lighting in public areas. We also propose educational programs on substance abuse, sexual violence, and counterfeiting, alongside mental health and sex education initiatives. Additionally, economic and vocational support is crucial, offering financial aid and job training during high unemployment or economic downturns. Lastly, providing accessible mental health services to the public, focusing on potential victims and offenders, is essential to address the psychological aspects of crime.

In summary, a collaborative approach that combines technological advances, educational initiatives, economic support, urban planning and mental health services can effectively curb the rise in unemployment-related crime. This comprehensive strategy is critical to maintaining public safety and ensuring the well-being of New York City residents.

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