Durham University

Department of Computer Science

Data Science Dissertation Project

Racial Bias in Predictive Policing Algorithms: Simulating Systems of Coevolution Between Machine Learning Model and Human Perception

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Abstract

Predictive policing algorithms such as those used throughout the US today have been shown to be racially biased. With location-based predictive policing tools in particular, it has been proposed that there exists a capacity for feedback within these algorithms which could lead to an exacerbation of such biases. This study will be taking a novel cultural evolution perspective in investigating how such systems of feedback might give rise to coevolution between model and human perception, thus potentially contributing further to such a feedback system. The effects of overcompensation and confirmation bias were investigated, using crime report data from the Chicago PD. Additionally, a rolling window was instituted, and its effects on the trajectory of racial bias evolution were observed. Furthermore, a proof of concept experiment was carried out using dummy data in order to test the validity of the approach utilized. Both overcompensation and confirmation bias demonstrated considerable effects on racial bias progression, even at modest parameter settings. Meanwhile, introducing a rolling window into simulations provided the capacity for such feedback to occur. Altogether, these findings highlight the desperate and urgent need for resolution of racial bias in current predictive policing algorithms, be it through model debiasing, police education, increased model transparency, or, failing these, a moratorium on the use of the technology – at least for the time being.

"Modelling the world as it is is one thing. But as soon as you start using that model, you are changing the world, in ways large and small. There is a broad assumption underlying many machine-learning models that the model itself will not change the reality it's modelling. In almost all cases, this is false."

– Brian Christian, The Alignment Problem (2021)

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Ancillary materials

Below are the links to both the R and Python code as well as the KNIME workflow used for and referred to in this report. Descriptions of methods used are generally kept at a high level throughout the report, and so referring to these resources is recommended.

R and Python Code: *github.com/cgribben1/Dissertation-Project-2023*

- `Exploratory_data_analysis.R`
- `Poisson_regression.R`
- `Negative_binomial_regression.R`
- `ZIP_regression.R`
- `ZINB_regression.R`
- `Model_validation.R`
- `Simulations.R`
- `Maps.R`
- `Dissertation.ipynb`

KNIME Workflow: *hub.knime.com/curtisg1/spaces/Public/latest/Dissertation~P0ZSoDm9z3pZ57T5*

1 Introduction

1.1 Background & Context

Today, Artificial Intelligence (AI) is finding greater application in crucial decision-making processes, spanning a wider range of domains than ever before. Alongside this rise, there is a burgeoning body of evidence illustrating AI systems' capacity to, in certain contexts, make biased decisions. Take mortgage eligibility estimators in the US for example. Several such algorithms have been found to be racially biased, proving more likely to deny a Black individual the same loan than a white individual, with all other factors kept the same (Martinez & Kirchner, 2021). Meanwhile, Amazon has recently had to discontinue an AI recruitment tool due to the presence of a gender bias against women within the algorithm (Parikh, 2021). These, however, are not the only areas in which such algorithmic bias is being identified.

“Predictive Policing” is a law enforcement strategy that utilizes data analysis and machine learning to predict, prevent, and respond more effectively to future crime (Pearsall, 2010). It is a practice which is becoming more widely used these days – predictive policing tools are thought to be used by police forces or courts in most US states (Heaven, 2020). However, a number of studies have shown that these tools have the capacity to perpetuate systemic racism (Richardson *et al.*, 2019).

Predictive policing can be broadly categorised into two forms: “Individual data-based” and “Location-based”. Arguably the most well-known individual data-based predictive policing tools is one used throughout the US named COMPAS (“Correctional Offender Management Profiling for Alternative Sanctions”). It is employed by various jurisdictions to assess the risk of recidivism (reoffending) among individuals who are involved in the criminal justice system, such as pretrial defendants and parolees. The risk score it outputs is then used to inform on important decisions such as the granting of pretrial release or parole. However, the risk scores outputted by the COMPAS algorithm have been shown to be racially biased; a higher risk score was observed being assigned to Black individuals than for White individuals, with all other factors kept the same (Angwin *et al.*, 2022).

The second type of predictive policing mentioned – and the one which forms the focus of this study – is that of location-based. Location-based predictive policing, sometimes referred to as “crime forecasting” aims to predict where and when crimes are likely to occur, allowing agencies to allocate resources more strategically. Location-based tools are currently in use across many countries, and are particularly prevalent within the US (Richardson *et al.*, 2019). “Geolitica” – a particularly prominent location-based predictive policing tool (formerly named “PredPol”) – is reported as currently being used to help protect roughly one out of every 30 people in the US (*geolitica.com*, 2023). Additionally, location-based tools are being used in Europe – “Precobs” assesses the likelihood that certain areas will experience burglaries, and is currently deployed in Austria, Germany, and Switzerland (Baraniuk, 2018). However, there is growing evidence that tools such as these, too, might be racially biased (Oswald *et al.*, 2018; Babuta & Oswald, 2019).

Location-based predictive policing relies heavily on historical crime data to identify areas with high crime rates. However, this data often reflects existing racial disparities in policing practices. There exists years of evidence suggesting that police officers – either implicitly or explicitly – consider race and ethnicity in their determination of which persons to detain and search and which neighbourhoods to patrol (Gelman *et al.*, 2007; Lange *et al.*, 2005; Bunting *et al.*, 2017; Mueller *et al.*, 2018; Levitt, 1998; Langan, 1995). Over-policing in minority neighbourhoods can result in an overrepresentation of crimes committed by racial minorities, which further perpetuates bias in predictive algorithms.

Predictive policing algorithms can inadvertently perpetuate racial bias when they incorporate biased historical data – a process generally termed “garbage-in, garbage-out” model biasing. For example, if the historical data shows a higher rate of arrests in minority neighbourhoods, the algorithm may disproportionately target these areas, even if the true crime rate is not higher. The result is that predictive tools misallocate police patrols: some neighbourhoods are unfairly designated crime hot spots while others are under-policed. (Heaven, 2021).

Then, as a result, racial bias already present in a predictive algorithm may be further intensified by the emergence of a feedback loop (Ensign *et al.*, 2018; Richardson *et. al.*, 2019). Police officers are deployed to predicted high-crime areas, resulting in increased police presence. This increased presence can lead to more arrests or crime reports, further skewing the data. As a result, the algorithm reinforces its own predictions, making it increasingly difficult to break the cycle of bias (Lum & Isaac, 2016).

In this way, the existence of such feedback loops effectively institutionalizes bias. As long as predictive policing algorithms continue to reinforce their predictions with biased data, the cycle of racial bias persists and may even amplify over time.

In this study, we aim to model the effects of such feedback loops of racial bias within location-based predictive policing algorithms. The details of the approach taken are set out in the following sections.

1.2 Utilizing A Cultural Evolution Framework

Empirical studies which model these proposed feedback loops are currently somewhat sparse within the literature, let alone those which do so taking into account factors of behavioural psychology and cultural evolution. Discussion on feedback loops so far has only concerned machine, and not human. That is, speculation has only considered the consequences for when police match more or less exactly the distribution strategy suggested by the predictive model (Richardson *et al.*, 2019; Ensign *et al.*, 2018; Lum & Isaac, 2016; Heaven, 2021).

Firstly, we will outline the proposed source of feedback for where suggested distribution strategy is matched by police. It is likely that forecasts output by a predictive model are already racially biased compared to the current strategy of police distribution. For example, police might allot resources between areas in an unbiased way, and the biased crime report data, in fact, originates from the increased likelihood of an officer apprehending Black vs non-Black individuals, per officer in a given area (Headley & Wright, 2020). If this is the case, and police departments use the predictive forecasts to inform on how they distribute resources, then racial bias is expected to increase, as police match the advised distributions suggested by of the forecast, which are biased simply from the differential propensity of officers to apprehend Blacks versus non-Blacks, independent of police distribution. Thus, even when police match the output forecast *exactly*, it could be possible for a feedback loop to form and for pre-existing racial bias in such predictive policing algorithms to deepen.

Further to this proposed process, we model the effects of when police do not necessarily exactly match the distribution strategy suggested by the predictive model. Such an approach has not yet been taken – feedback loops of racial bias in predictive policing algorithms have not yet been looked at from a cultural evolution point of view. This paper will investigate the possibility of a system of coevolution between machine learning algorithm and humans' perception. It is proposed here that such a feedback loop of intensifying racial bias might be further exacerbated by the role of human agents and their range of internal cognitive biases and irrational behaviour. Here, we will investigate the effects of two common modes of irrational behaviour within behavioural psychology: "overcompensation" and "confirmation bias".

Behavioural biases can lead to us misinterpreting information around us, and can lead to irrational actions. One way in which this might happen, within this particular context, is overcompensation. Applying the general concept of overcompensation to the particular system proposed here, we posit that police might allot disproportionately more resources to a given area if the crime rate of that area, as forecast by the predictive model, is above the total mean crime rate. In other words, it is suggested here that police will send even more resources than the model suggests, if the model deems a given area above average in terms of expected crime rate. The reverse is also suggested – that disproportionately fewer resources will be sent to areas deemed to have a below average expected crime rate. Note that a higher forecast might lead to not just an increase in the number of officers sent to a certain district, but also an increase in the likelihood, per officer, of a crime being reported, given the potential heightened sensitisation due to the forecasted crime risk. Thus, extra power is given to the proposed effect.

Also investigated here is the effect of confirmation bias. Confirmation bias is defined as the tendency to interpret new evidence as confirmation of one's existing beliefs or theories. Within the specific context of this study, we propose that it might manifest in police officers picking up on an increase in crime rate of a given area, following the effect of overcompensation – if, for example, a given area has increased in reported crime rate compared to last year, officers may notice it having done so, and, thus, be more inclined to send more resources to the area than the predictive policing model suggests. Once again, the reverse is true for areas that might have decreased in crime report rate since the previous year. Also, the per-officer likelihood of a crime being reported would likely be affected, too, by this behavioural bias.

In this way, the proposed effects of both overcompensation and confirmation bias compound – this is visualized in the explanatory diagram below (**Figure 1**), which describes the system to be investigated in this study.

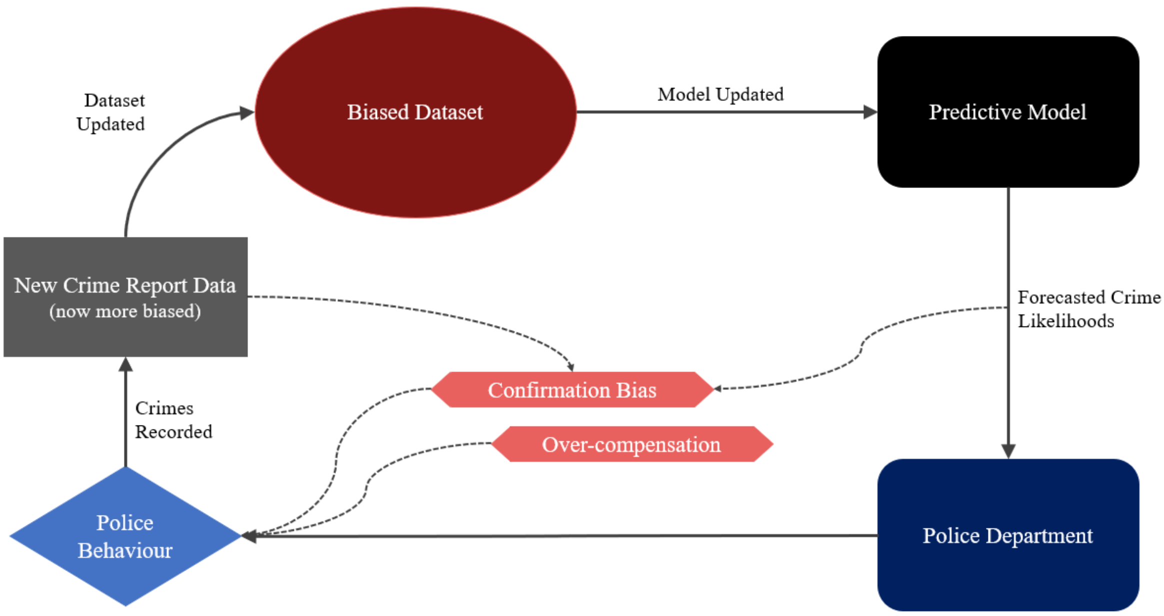


Figure 1. Diagram showing logic of proposed coevolutionary feedback system.

1.3 Research Scope – Chicago

Chicago is one of the largest and most racially segregated cities in the US (*southsideweekly.com*, 2022). Being such a large city, there exists an abundance of crime data available for analysis. Furthermore, there exists a multitude of evidence for the presence of racial bias and over-policing of Black populations in Chicago. In the points below, we outline just some of this evidence. Note that although project will focus on racial bias toward Black populations, similar inferences might be taken from its findings to inform on patterns of bias toward other minority races.

(*northwestern.edu*, 2020) – "Black and Latinx people in the United States, especially those living in low-income and segregated neighbourhoods, disproportionately encounter police and experience higher levels of harassment, intimidation, and violence during those encounters."

(*lawreview.uchicago.edu*, 2022) – This essay discusses how Chicago police criminalise Black areas, referring to the Supreme Court's decision in Illinois v. Wardlow of granting police significant discretion to stop people in areas that they define – often inaccurately, according to some research – as having high levels of crime.

(*news.wttw.com*, 2022) – "Chicago Police were more likely to stop Black Chicagoans than White Chicagoans and more likely to use force against them, according to an audit"; "When a police stop results in an officer using force against a Chicagoan, 83.4% of those incidents involve a Black person (…) However, the people of Chicago are 31.4% White, 29.9% Latino, 28.7% Black and 6.9% Asian, according to the 2020 U.S. census."

(*aclu-il.org*, 2022) – "Black and Latinx drivers in Chicago are stopped and searched at traffic stops at far higher rates than white drivers."; "In 2021, Black drivers were more than 5 times more likely to be stopped by CPD than white drivers."

(*igchicago.org*, 2022) – "Black people were overwhelmingly disproportionately stopped by CPD, regardless of the demographic composition and crime level in the district of the stop, both in investigatory street stops and at traffic stops. Furthermore, given that they were stopped, Black people were significantly more likely to be treated with force than non-Black people – Black people were 11.7 times more likely to face a use of force following an investigatory stop than non-Black people."

Thus, it is easy to see that Black populations are considerably over-policed in Chicago – they are stopped disproportionately more frequently and treated with greater force than non-Blacks during police interactions. This will inevitably result in a Black individual being more likely to be included in a crime report than a white individual. Therefore, given the totality of the available evidence, it is extremely likely that there exists a significant racial bias toward Black individuals in the dataset being analysed – this observation sets up the assumed starting condition for the model, and, thus, provides the basis for the study.

It is worth noting that race has also been linked to poverty rates in Chicago – poverty rates have been shown to be higher among Black residents compared to other racial and ethnic groups in the city (Hwang & Sampson, 2014). In the United States as a whole, there has historically been a correlation between areas with a higher Black population and higher poverty rates. This correlation has its roots in a complex history of systemic racism, economic disparities, and social inequalities. However, it's important to note that correlation does not imply causation, and the relationship between race, poverty, and other socio-economic factors is multifaceted and influenced by various historical, social, and economic factors, which tend to result in higher crime likelihoods (Shapiro, 2004). As a result, Black population percentage might be positively correlated with crime rate due to two different, but not unrelated mechanisms: (i) Black individuals are targeted disproportionately more by police forces, resulting not in more crimes, but in more reported crimes, compared to non-Black individuals; (ii) taking Black population percentage as a proxy for poverty rate, districts with a higher percentage of Black individuals might see an actual increase in crime occurrence (once again, due to unfavourable socioeconomic conditions experienced by such minority races throughout the history of the US). The former reason is that which forms the basis of this study, and although the latter might contribute to the crime rates observed, as long as the former contributes any effect to the crime rates observed, such an effect can be considered racial bias in crime reporting, and this effect of racial bias will be captured in our modelling and simulations.

Thus, while not explicitly described in the data, race is implicitly represented in the data, through a mechanism known as redundant encoding. Here, Black population percentage of a district is not taken in by the model but is nonetheless correlated with crime rate and is therefore inferred by the model. Whilst this would be acceptable if this metric was correlated only with crime reports as a result of crime occurrence, however – as already evidenced –, it is clearly the case that Black population percentage also correlates with crime reports as a result solely of over-policing.

In this study, we use Chicago crime report data in order to compare crime rates between districts. In doing so, we investigate several research questions and hypotheses – these are detailed in the section below.

1.4 Research Questions and Method Overview

The primary hypothesis investigated in this study, and its logic are detailed in the following:

- District black population percentage is significantly correlated to reported crime rates.
- This is because Black populations are significantly over-represented in crime reports, due to historical and institutional racism.
- Therefore, high-crime rate districts can, in general, be considered so because of their high Black population.

- As a result of overcompensation and confirmation bias, police will distribute disproportionately more resources to districts with forecast crime rates above the total mean, and less to those below the total mean.
- Reported crime rates for areas with above-average crime rates will then become even higher than the already biased baseline, compared to those with below-average crime rates, which will likely become lower than the starting condition.
- This now further biased data is fed back into the model, resulting in a now further biased crime forecasting model.
- Thus, the ratchet is turned, and the system of positive feedback continues.
- Therefore, as a result of the use of predictive policing forecasts, as well as the action of behavioural bias on their outcomes, racial bias is exacerbated in the model, and also to an extent in the police force.

In order to investigate this hypothesis, we first set out to construct a predictive model which will serve as an imitation of those currently used. For this, we look primarily to Geolitica, whose predictive tool reportedly uses only 3 data points – "crime type, crime location, and crime date/time" – to create its predictions. Therefore, will use crime location, and crime date/time data; we will not be splitting predictions by crime type, as this is neither overly relevant for the purposes of this study, nor reasonably feasible.

Using this model, we then go on to simulate consecutive years of crime report data, in order to investigate patterns that may arise in racial bias within the model. Using a cultural evolution framework, we factor in and test the effects of two behavioural biases: overcompensation and confirmation bias.

Additionally, we investigate the effects of instituting a rolling window during simulations. It is expected that any effects observed on racial bias will be diluted if not using a rolling window, compared to when using one. It is presumed that, in general, police forces use rolling windows, as this allows for the predictive model to remain up to date, and thus more accurate. There is a great deal of justification for this presumption; crime rates have been shown to change over time overall, as well as between areas, and therefore there is a significant need for such an algorithm to be up to date, while there is proof that taking a smaller window does not negatively affect model accuracy (Feng *et al.*, 2019).

We also make and run in simulations a proof of concept model by using dummy data, in order to add validity to our approach by proving that any signal observed comes solely as a result of the effects intended for investigation in this study.

Finally, we construct a spatiotemporal visualization of the simulated crime patterns in Chicago.

1.5 Key Project Aims

Below are the key aims of this study, summarised at a high level. In the following, we attempt to:

1. Emulate a location-based predictive policing machine learning model using Chicago crime data. It is expected that this will mirror the inherent racial bias already present in the crime data. This model will act as a "best guess" of current algorithms being used.

2. Run simulations using this model, spanning multiple years, to elucidate the system's capacity for the deepening of racial bias, factoring in the effects of two behavioural biases: overcompensation and confirmation bias.

3. Introduce a rolling window to investigate how this might affect the system's capacity for a feedback loop of amplifying racial bias.

4. Carry out the above steps using randomly generated dummy data as a proof of concept. This will prove that the effects observed are a result only of the conditions investigated here, and not from any incidental mechanisms at play in the data.

5. Provide a spatiotemporal visualization of the simulated crime patterns in Chicago.

2 Methods

2.1 Data Preprocessing and Exploratory Data Analysis

2.1.1 Loading and Cleaning the Data

The dataset used was extracted from the Chicago Police Department's CLEAR (Citizen Law Enforcement Analysis and Reporting) system (cityofchicago.org, 2023) and describes reported incidents of crime (with the exception of murders where data exists for each victim) that occurred in the City of Chicago from 1st January 2001 to 31st January 2017. The total number of unique observations in this dataset is 6,154,003 (this represents the number of unique crime reports recorded). Full column descriptions of this dataset are given in **Appendix 1A**. One point worth noting, however, is that values of the "`Date`" column reportedly can be a "best estimate" of the time and date. This means that some values won't represent an accurate account of when the crime occurred. On the other hand, given the size of the dataset and the assumption that the expected effect of this will be consistent across all reports, we should still see a true reflection trends in crime reports over time across districts.

The raw data was downloaded in four separate files: data collected during 2001-2004, 2005-2007, 2008-2011, and 2012-2017. These were each read into a KNIME software environment for data cleaning. Following standardisation of column formats, removal of duplicate rows, column filtering, and column renaming, these four dataframes were then concatenated together to form one dataframe. Two districts ("21" and "23") had noticeably limited observations (n < 5) and were therefore excluded from analysis. Additionally, there is no district "13" in the dataset. This is because there are no districts "13", "21", or "23" in Chicago, due to historical reorganisation (chicagopolice.org, 2023). Thus, there were 22 police districts included in this analysis. It was decided to use all crime reports as the response variable, and not just those which resulted in an "arrest". This is firstly because this strategy gives more observations and will therefore lead to a more accurate predictive model. Secondly, the ultimate goal of such a model is to predict where incidents to which police are required to respond are likely to occur; not just at which an arrest is required to be made (Heaven, 2020). Additionally, it is suggested that arrest data might be even more racially biased than crime report data (Heaven, 2021), given that Black individuals are more likely to be arrested than non-Blacks once confronted by police (Headley & Wright, 2020). It, then, is reasonable to assume that departments such as CPD who might use predictive tools such as Geolitica might make the same decision, in order to maximise accuracy and practicality of real-time prediction, while minimizing (as best as possible between the two choices) the capacity for racial bias. Further, rows were excluded which correspond to locations at which crimes are unlikely to be detected by police patrols. This was done because the purpose of the model is to emulate those being used by police forces in the real world, and, thus, to forecast where police patrols might be best used to detect and deal with crime. Therefore, crimes such as those which take place within domiciles and business-places were excluded from analysis (see **Appendix 2** for list of excluded "`Location Description`" values). Following this, "NA" values were excluded from the dataset.

By this stage, one variable ("`district`") from the original dataset had been retained for model-building, with five new variables, having been engineered as features from the original "`Date`" column, also included ("`year`", "`month`", "`date`", "`hour_of_day`", "`day_of_week`"). See **Appendix 1B** for descriptions of newly engineered predictors.

It was noticed that the number of crime reports during the last few days of December are very low, and also that there's a small spike in reports in mid-January. The reason for these could be that crime figures aren't fully updated in late December, causing a backlog which is cleared through in January, resulting in an artificial spike in crime count. Alternatively, this pattern might represent actual fluctuations in crime rates. As will be further detailed in the results section below, the drop in crime rates here may be due to a change in patterns of human behaviour during the holiday season. Due to the causal ambiguity surrounding this trend, it was decided to keep the values as they are, and thus it is assumed that the observed trend reflects real-life fluctuations in crime rates. Furthermore, crime counts for January 1st, March 1st, and June 1st appear abnormally high; the exact reason for this is not known and might be a result of data submission practices – perhaps crimes with unknown dates are assigned to these days, or perhaps these represent deadlines for periodic report submission, which results in a spike in reported crimes as backlogged reports are assigned the date of the deadline. Alternatively, however, it may be that these represent real rises in crime reports, potentially due to annual police force initiatives or audits causing a temporary rise in crime detection and/or reporting. Without further investigation into or consultation with the CPD regarding crime reporting practices, the reason for these spikes in reported crime will not be known. Nonetheless, for the purpose of this study, it will be assumed that these spikes are artificial ones and that they do not represent a true increase in crime rate; therefore, the anomalous date has been adjusted. These outliers were transformed to match the mean of the directly neighbouring days, redistributing randomly the deficit amongst the remaining days in the month. For this, a custom Python function was built, which utilized modular arithmetic methods as well as the "`randint()`" function to iterate through the reports of each of the relevant days, and to reassign the dates of a certain proportion of these to random dates within the same month.

2.1.2 Black Population Percentage & Crime Rate

The first relationship to be described, and arguably the most striking, is that between district Black population percentage and crime rate (henceforth, and unless otherwise specified, "crime count/rate" will be used to refer specifically to "crime *report* count/rate"). Correlation analysis revealed a strong positive correlation between the two variables (Pearson's $r = 0.808$, $p < 0.0001$). Additionally, a linear regression model was fitted to the data, and it explained a substantial portion of the variance in district crime rate (Adjusted R-squared = 0.635, $p < 0.0001$). A plot of this relationship is shown below in **Figure 1**.

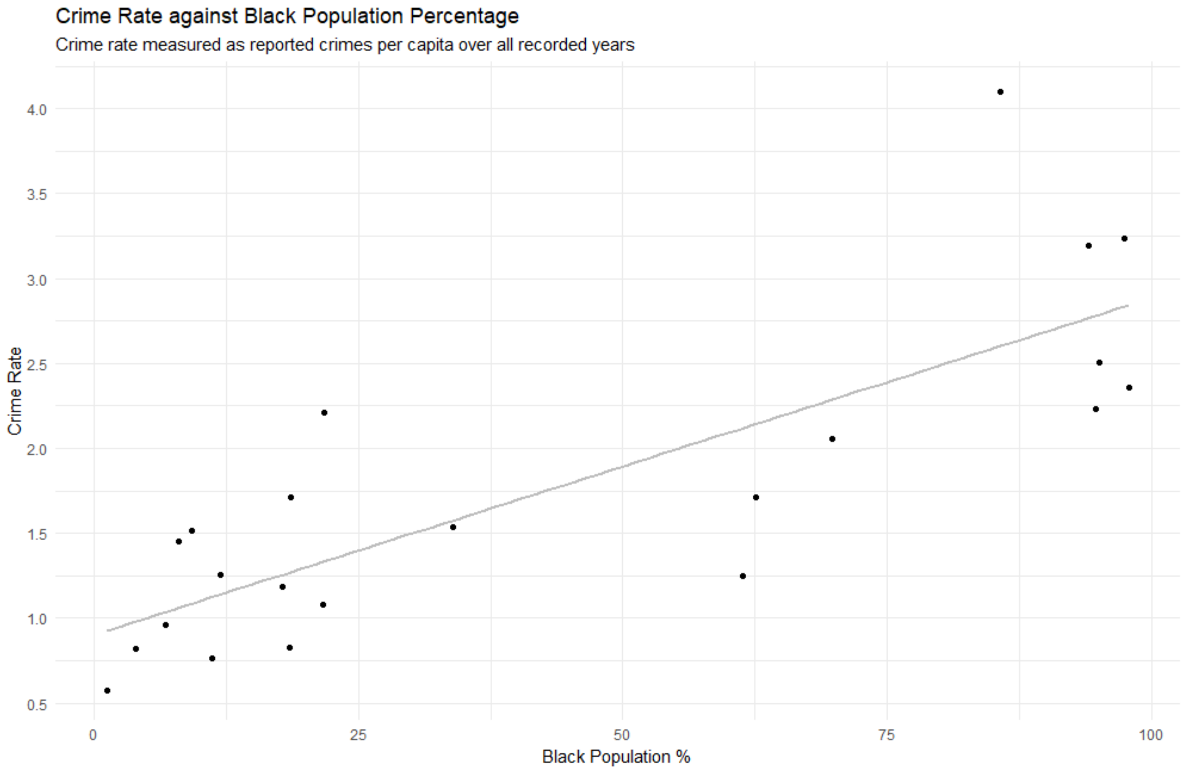


Figure 1. District Crime Rate against Black Population Percentage.

The demographic data used here is taken from the 2010 US Census data on race and ethnicity (*johnkeefe.net*, 2023). Note that this comes with the caveat that the demographic data used for these statistical calculations was taken from just one year (2010 US Census data on race and ethnicity), and so it is assumed here that the demographics data remains the same over the years used in the above calculations, or at least roughly represents the mean demographic data of the time range studied (2001 – 2017).

This trend will form the basis of this study, and it is be assumed that a proportion of the effect of Black population percentage on district crime rate comes as a result of inflated crime report rates due to the over-policing and subsequent over-reporting of Black individuals in crime reports.

2.1.3 Crime Rate by Day of Year

Next, the effect of day of year on crime rate was investigated. In the figures below, crime count is shown plotted by day of year. Note that crime count and crime rate are directly equivalent, as all crime count values are divided by the total population to find crime rates; therefore crime count is shown here, however either metric would show the same trend. **Figures 2a** and **2b** show crime count per day of year for before the correction of anomalies and for after this correction, respectively.

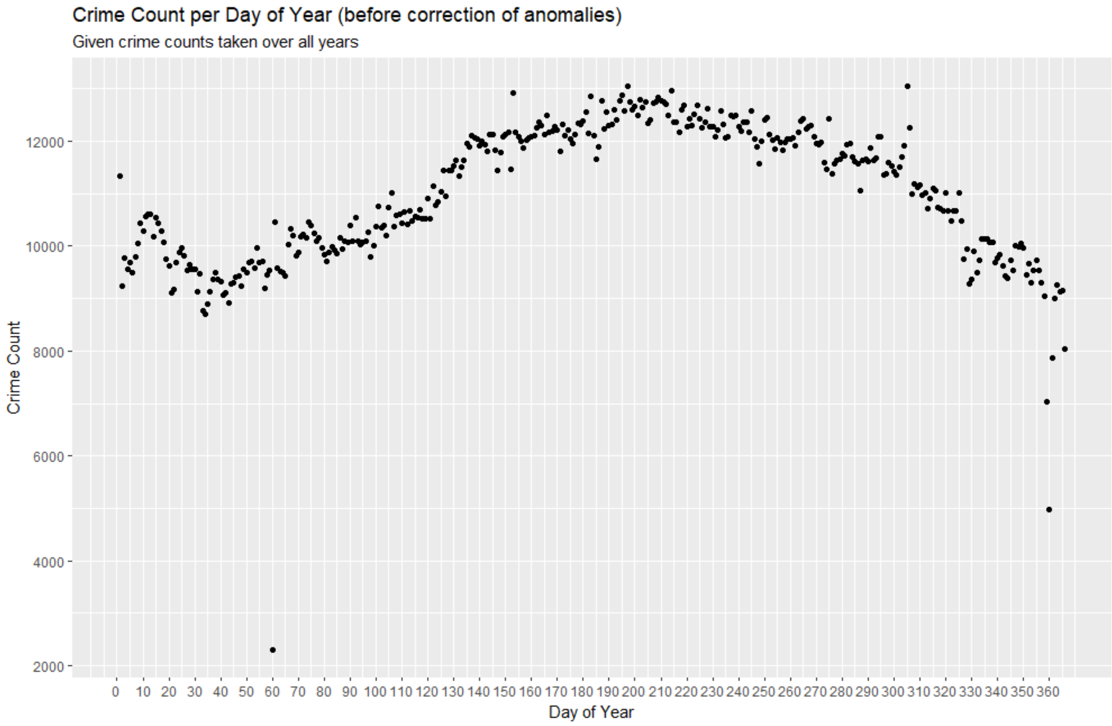


Figure 2a. Crime Count per Day of Year, before correction of anomalies. Shown here are the days between 1st January 2001 and 31st December 2016 – this was done so the extra days in January 2017 don't augment visualization of any trends.

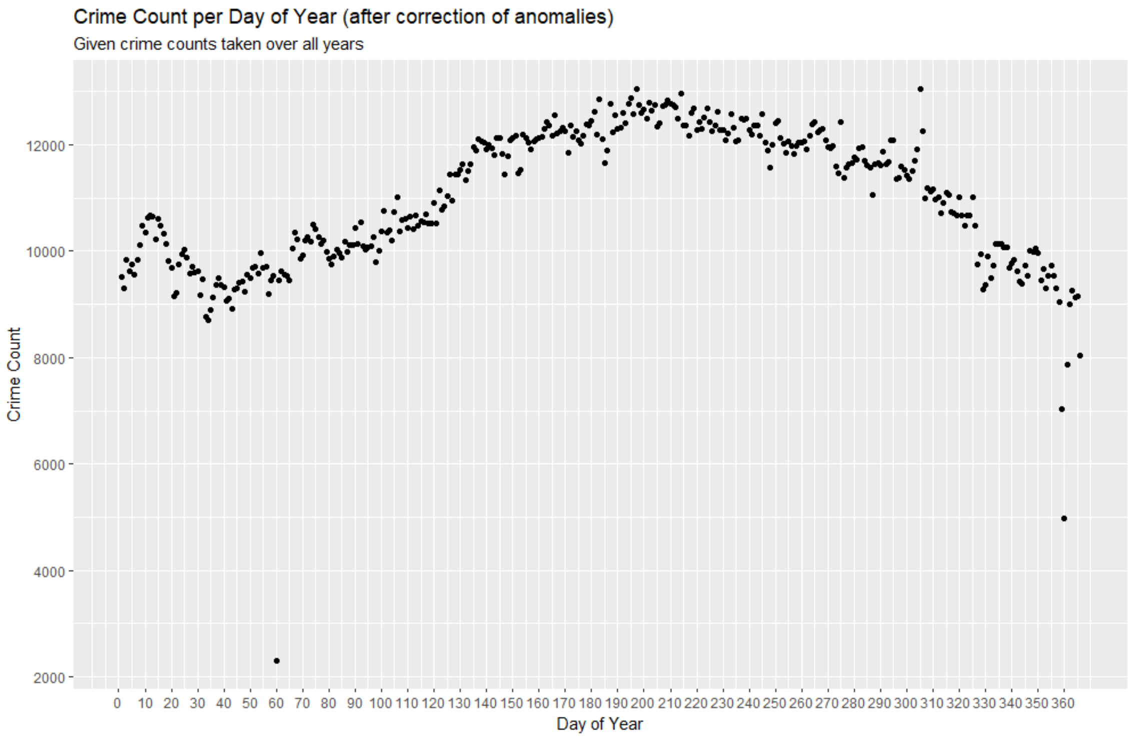


Figure 2b. Crime Count per Day of Year, after correction of anomalies. Once again, data shown are from between 1st January 2001 and 31st December 2016.

Firstly, it must be noted that, given that the response variable comes in the form of count data, the dataset doesn't meet ANOVA assumptions for testing for a significant effect from a given predictor variable on the response variable (see **Appendix 3** for Q-Q plot showing non-normality of the crime count data). Instead, the test statistics for the rest of this section are derived from a Negative Binomial regression model. Here, a Wald test is carried out for each predictor variable, to test whether the coefficient the predictor is significantly different from zero. These test statistics can be viewed in the output of the "`summary()`" R function when applied to the model. The model in question is a provisional model formed using all variables described below (a fully optimised model was later used for simulations, and its inception detailed in **Sections 2.2** and **3.1** below). Note that due to the fact that the variables used are categorical, the returned summary statistics are those of the corresponding dummy variables – one for each level of every predictor. The model was constructed using all possible predictor variables in order to account for any confounding effects, so that as true a picture as possible might be observed of the relationships of each predictor with crime count. Thus, the P-values reported for each predictor variable throughout this section will be those corresponding to a Wald test for each level of the variable – these can all be found in **Appendix 4**.

As can be seen in the graphs above, day of year has a significant effect on crime count ($p < 0.05$ for a majority of the encoded dummy variables, using reference level of "01-01"). The most notable trend in this relationship is that crime rates rise significantly during the middle of the year. This is a widely observed trend throughout society (Linning, 2015), and there are several hypotheses that seek to explain this change in crime rates – these will each be detailed here.

Hypothesis a) Hours of daylight – longer daylight hours during the summer provide more opportunities for people to be outside, leading to increased social interactions. This can create more opportunities for crimes to occur, such as street crimes and property offenses (Doleac & Sanders, 2015).

Hypothesis b) School summer vacations – summer vacation results in school students spending more time outside of school. Thus, idle youths may be more prone to engage in delinquent or criminal behavior during this period (McDowall *et al.*, 2012).

Hypothesis c) Increased temperatures – as temperatures rise, many people are generally uncomfortable. This discomfort can give rise to aggression which could lead to aggressive criminal activity (Field, 1992). Chicago is known to experience hot summers, with a July daily average temperature of 24.8°C between the years 1991 and 2020 (National Climatic Data Center, 2021). Conversely, Chicago's experiences cold winters (National Climatic Data Center, 2021); this might discourage certain types of criminal activities or make them more challenging to carry out.

Hypothesis d) Tourists and visitors – more, new, and naïve individuals present increased opportunity for crimes such as petty theft and scams (Altindag, 2014).

Hypothesis e) Alcohol consumption – during the summer, people often participate in outdoor gatherings, parties, and events, where alcohol is often consumed. This could contribute to an increase in crimes related to public intoxication, DUIs, and alcohol-fuelled disputes (Gorman *et al.*, 2001).

In addition to this overarching trend, there are several other notable trends that can be seen in the relationship between day of year and crime count. For example, there is a large spike in crimes in the days around Halloween (October 31st). This is likely due to increased alcohol and drug consumption, and the fact that people tend to go out at night to socialise more than usual around Halloween (*attorneyshartman.com*, 2021). Splitting out crime count by crime type (see **Figure 3** below), we can see a large spike in battery crimes during this time of the year – a rise in this particular type of crime is consistent with this hypothesis.

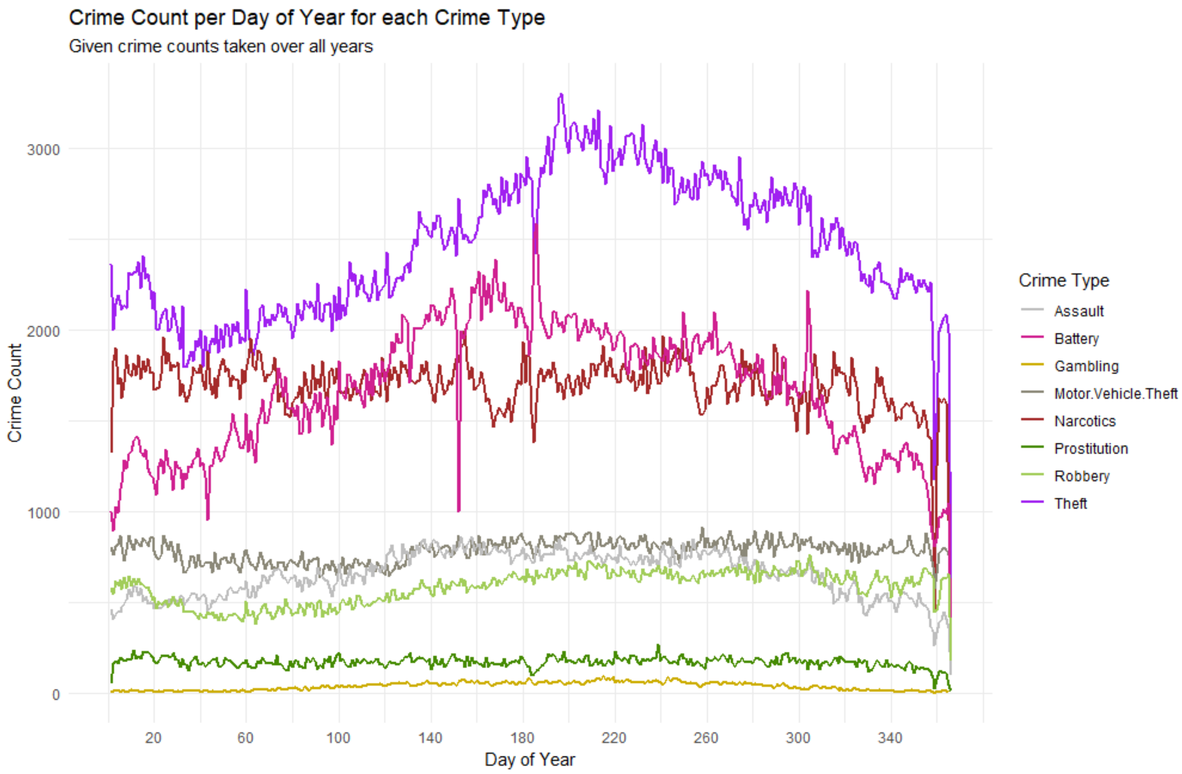


Figure 3. Crime Count per Day of Year split by crime type. Data shown are from between 1st January 2001 and 31st December 2016. Additionally, February 29th was left out to produce a clearer visualization of the trend. Crime types shown are the eight most common found in the dataset.

Additionally, there is a slight drop in crimes during the last week of November. This is likely due to Thanksgiving, which occurs every year on the fourth Thursday of November. Additionally, there are fewer crimes on Christmas Day (as well as Christmas Eve and Boxing Day). This may be due to the holiday season, where many people take time off work or school to spend time with their families and friends. Increased social gatherings and festivities can lead to a decrease in criminal activity as people focus on celebrating and relaxing rather than engaging in unlawful behaviour.

Although it doesn't seem to greatly affect overall crime count, there are some noticeable changes in certain crime types around the 4th of July (a major holiday in the US). Around this day, theft and narcotics crimes experience a significant drop, while battery sees a considerable increase. These changes in crime count seem to roughly balance out at the overall level.

Note that there is a particularly low crime count for 29th February – this is because, being a leap day, it comes only once every four years, and therefore experiences roughly a quarter of the recorded crimes compared to other days.

2.1.4 Crime Rate by Hour of Day

Hour of day has a very strong effect on crime rate, as can be seen in **Figure 4** below. Although the variable tested was only that at the "half-day" level, the "`hour_of_day`" value of "2" displayed a significant effect on crime count compared to the reference level of "1" ($p < 0.001$).

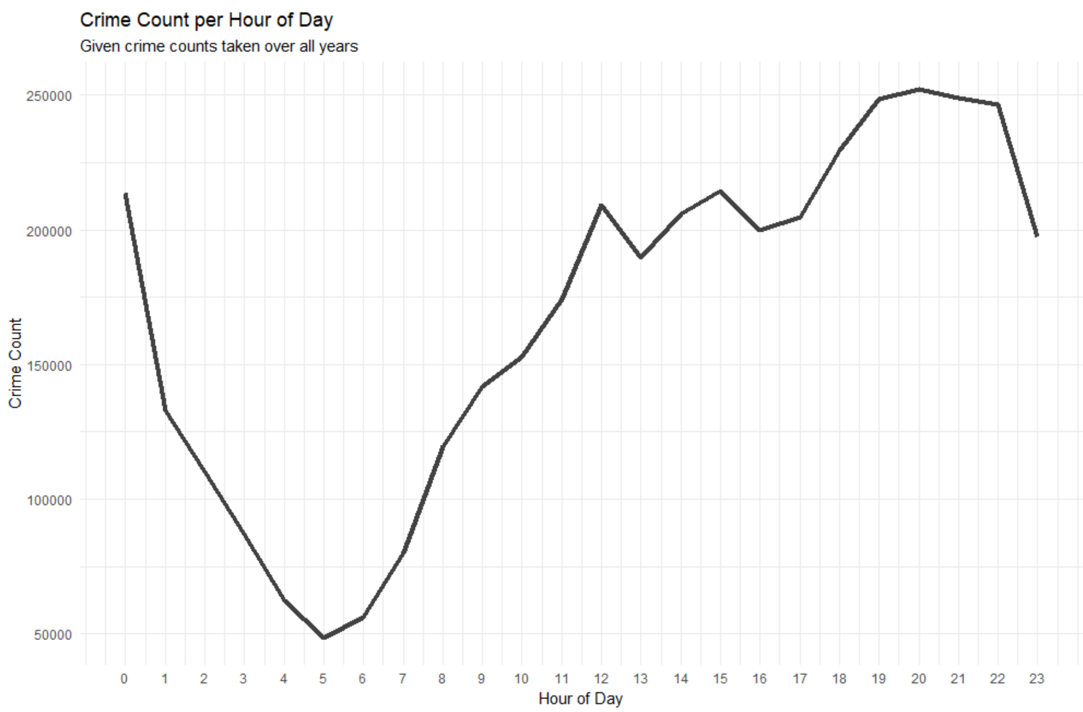


Figure 4. Crime Count per Hour of Day.

As a general trend, crime count is lower during the first half of the day than in the second half, being the lowest around 04:00 – 06:00, and the highest around 19:00 – 22:00. Again, several hypotheses behind explaining this trend will be outlined below.

Hypothesis a) Routine human activity – the trend generally aligns with rates of human activity over the course of the day, where opportunities for crime differ depending on the hour of day and distribution of human activity (Cohen & Felson, 1979; Clarke & Felson, 1993).

Hypothesis b) Darkness and visibility – criminals may feel less exposed and have a greater chance of evading detection, thus may be more likely to commit crimes during hours of darkness (Cohen & Felson, 1979).

Hypothesis c) Circadian rhythms – human behavior, including criminal behavior, can be influenced by circadian rhythms, which are natural, internal processes that regulate the sleep-wake cycle and physiological functions. Some studies suggest that crime rates might be higher during evening and nighttime hours when offenders may feel more active and less inhibited (Levandovski *et al*., 2011).

Hypothesis d) Alcohol and drug consumption – these tend to take place in the evening hours, and generally lead to increases in impulsive and aggressive behaviour; this can contribute to higher crime rates during these times (Brinkley-Rubenstein & Taylor, 2014).

Hypothesis e) Time-associated crime types – some crimes tend to occur mainly at certain times. For example, as we can see from **Figure 5**, crimes such as prostitution and gambling occur almost exclusively at night and in the early morning; this is likely because of the nature of such crimes (Dalla, 2002). Note the uptick in prostitution around 07:00 – this might be due to participants being reprimanded upon leaving premises following the act.

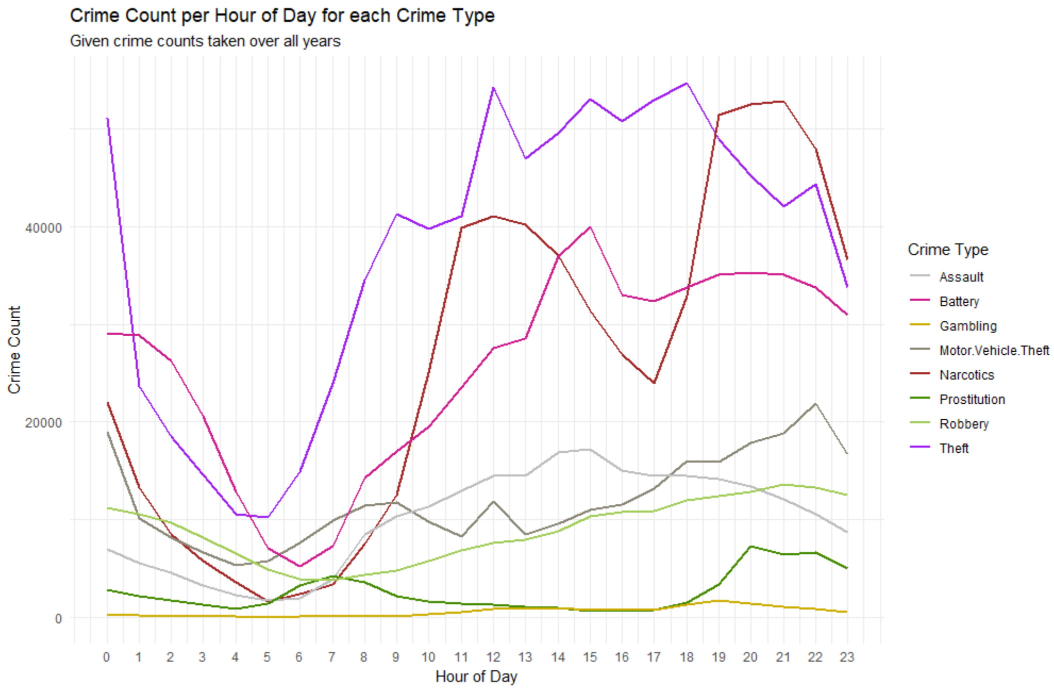


Figure 5. Crime Count per Hour of Day, split by crime type.

Here we see a possible contradiction between the "hours of daylight" hypothesis and "darkness and visibility" hypothesis. A resolution to this which maintains the validity of both hypotheses might be that all days, naturally, have a nighttime, and so will always enjoy the boost in crime in the evening. However, summer days also have the added boost of longer sunlight hours therefore more crime leading up to the nighttime. In other words, the effect of nighttime on crime rate is uniform between days of the year; it is independent of night length.

Note also the minor peak in crime rates at 12:00. It is proposed that this is an artificial peak, created by reporting officers defaulting to this time within reports out of convenience and/or uncertainty. This might also be the case with the minor peak at 15:00 – perhaps police tend slightly more toward these three hour increments for reporting crimes between 12:00 and 18:00. It will be assumed that the effect of this is constant throughout districts, and therefore the effect can be disregarded for the purposes of this study.

2.1.5 Crime Rate by Month

Below in **Figure 6** is a graph showing the effect of month on crime rate (crime count per month per year). This shows the same trend as day of year against crime count; the data are simply grouped at a higher level. Nonetheless, the levels of the variable all displayed a significant effect on crime count compared to the reference level of "1", representing "January". Further, ten out of eleven of these returned a result of $p < 0.001$.

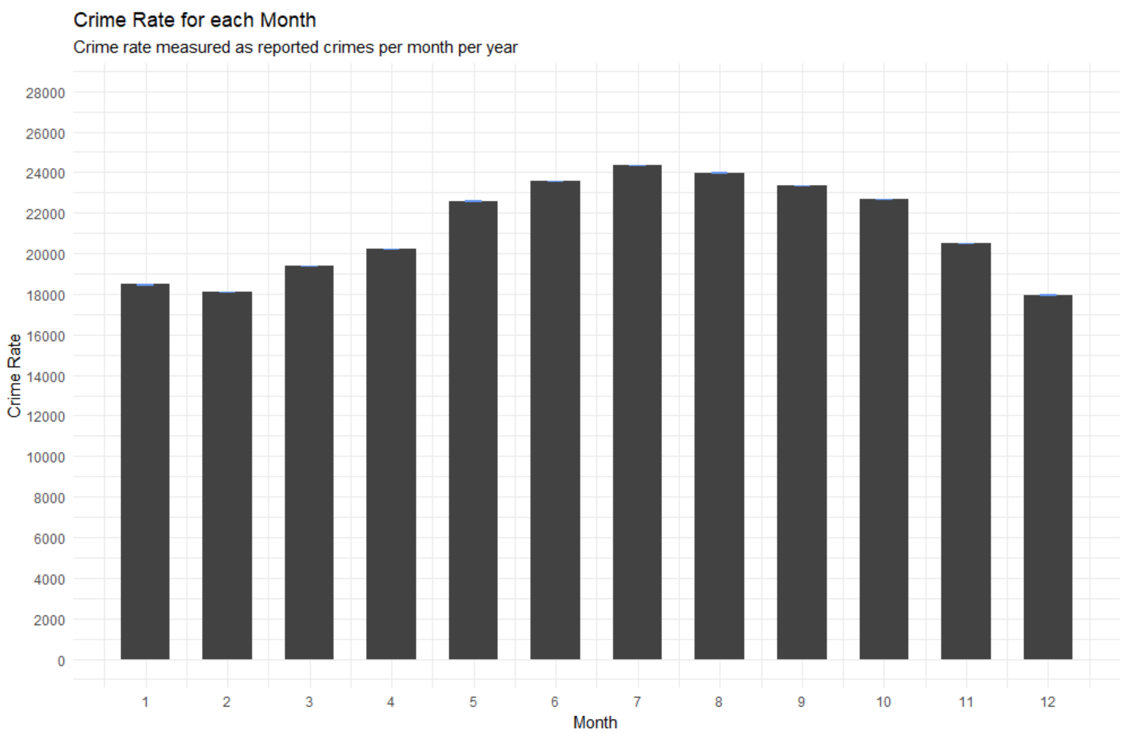


Figure 6. Crime rate per month. Crime rate measured as reported crimes per month per year. 95% confidence intervals shown in blue.

2.1.6 Crime Rate by Day of Week

Graphed below in **Figure 7** is the relationship between day of week and crime rate. Here we can see a comparatively weak, yet still robust effect between the variable levels ($p < 0.001$ for all levels, compared to reference level of "1", representing "Monday").

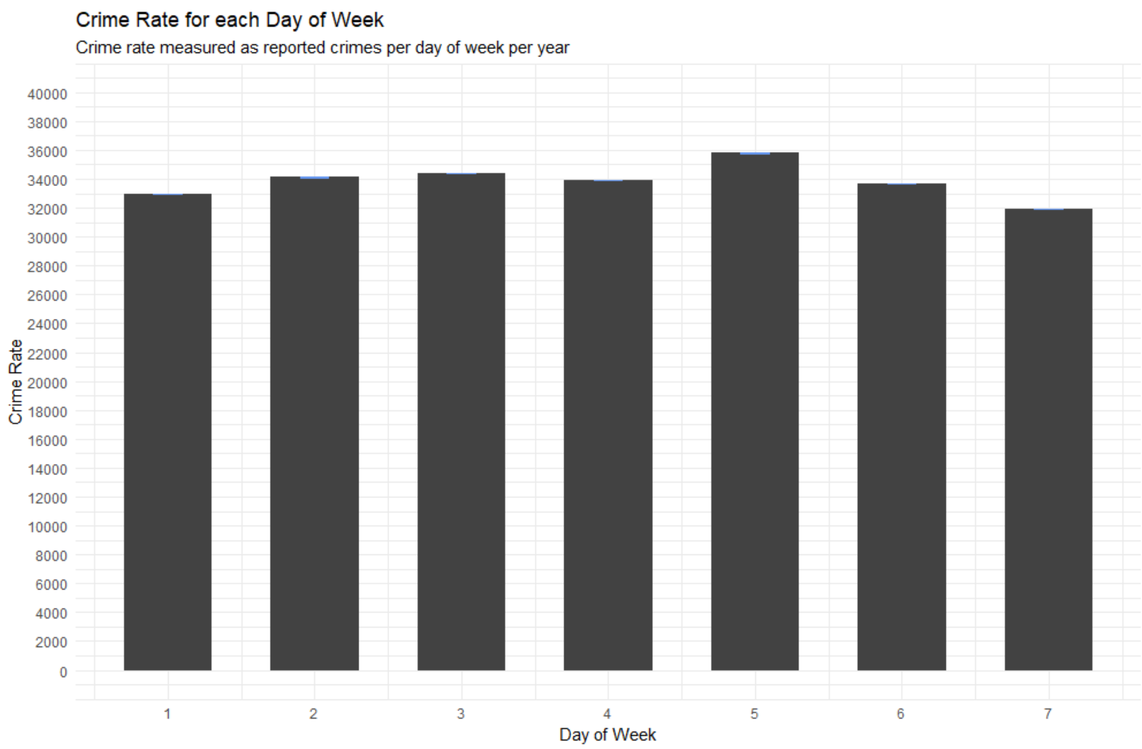


Figure 7. Crime rate per day of week. Crime rate measured as reported crimes per day of week per year. 95% confidence intervals shown in blue.

The trends observed here seem to align with several of the hypotheses already mentioned, for example those of "routine human activity" and "alcohol consumption". Looking at alcohol consumption in particular, the higher crime rates during Fridays and Saturdays might be explained, given that these are the two days of the week during which most alcohol (and drug) consumption generally takes place in the US (Lau-Barracco, 2016; Voas, 2013). In contrast, the day with the lowest crime rate is Sunday. This is likely because individuals tend to stay in and relax more on this day, therefore resulting in less opportunity for crime.

2.1.7 Crime Rate by Year

Finally, the relationship between year and crime rate (crime count per day) was investigated – this is shown below in **Figure 8**.

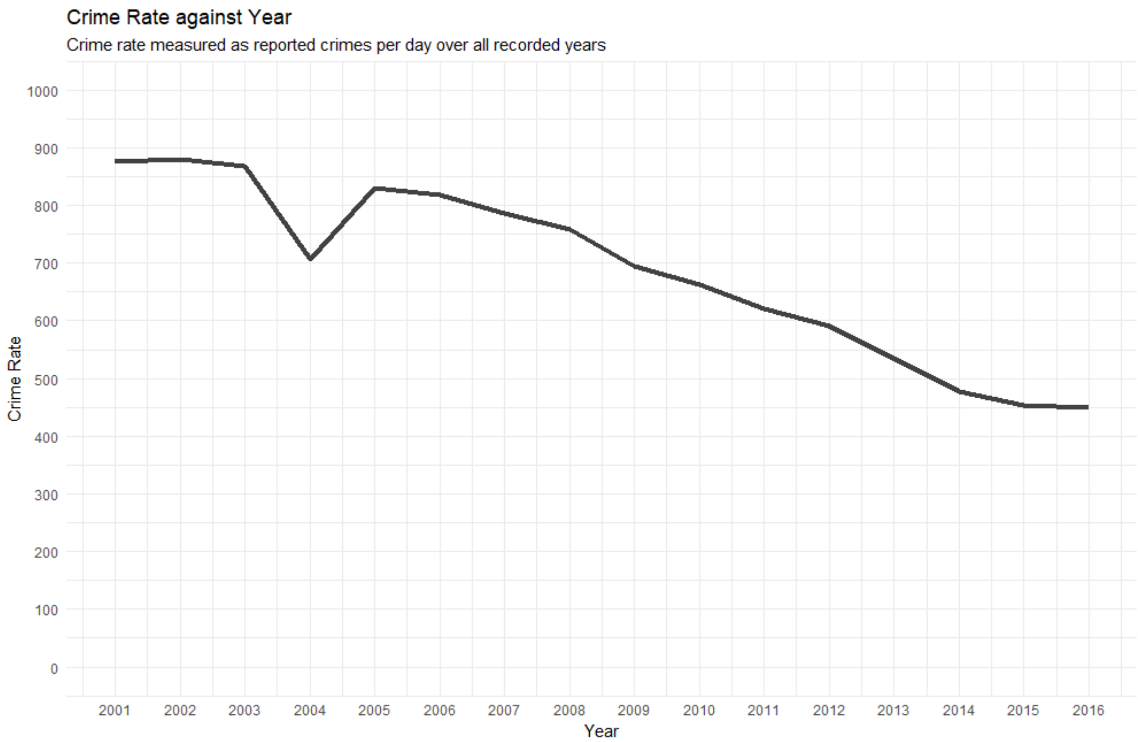


Figure 8. Crime rate against Year. Only full year data was used here, therefore the year 2017 is not represented.

It can be seen clearly that crime rate generally drops over the years within this timespan. This aligns with the general trend in crime rates across the US since roughly 1990 (Ouimet, 2004: Butts & Evans, 2014). There are several proposed explanations for this trend – these include economic improvement, demographic structure changes, changes in policing strategies and criminal justice policies, gun control measures, and technological advances (Levitt, 2004: Blumstein & Wallman, 2000; Zimring, 2007; Cook & Ludwig, 2006). For Chicago specifically, there is compelling evidence that crime rates are affected by neighbourhood gentrification levels (a proxy for economic improvement) (Papachristos *et al.*, 1991).

Also notable is the presence of a sharp dip in crime rate in 2004. This could be due either to change in practice regarding crime reporting or to an actual decrease in crime, due perhaps to introduction of policing initiatives, or an improvement in socioeconomic conditions.

2.1.8 Grouping the Data

Following this initial investigation, dataset rows were grouped by each possible time point at each possible district (i.e., they were grouped by "`district`", "`year`", "`month`", "`date`", and "`hour_of_day`"), thus creating a new column named "`crime_count`". To account for timepoints with zero reported crimes, corresponding rows were added into the now grouped dataset by creating a list of all possible timepoints and districts (n = 3,095,136) with "`crime_count`" set to "0" for all rows. A full outer join was then performed between this dataframe of possible timepoints and the main dataframe, giving a dataframe in which each row represents each possible timepoint and district, along with the recorded crime count for that instance. In doing so, 1,124,413 rows of zero counts were added to 1,970,723 rows of non-zero counts, giving a total of 3,095,136 possible timepoints across 22 districts (140,688 timepoints per district). The mean crime count of these timepoints was 1.300 and variance 2.084. Note that only data up to and including 18th January 2017 were used – this is due to the sparse nature of crime data between 19th and 31st January 2017 (as a result, 32 observations were omitted). This is likely a fill-rate issue; it may be that at the time when the dataset was uploaded, a significant portion of crime reports recorded as having occurred during the last few days before the cut-off were potentially not yet updated onto the system. Ultimately, therefore, a sum of 4,026,035 individual crime report observations were used for model construction.

Initially, the variable "`hour_of_day`" represented each hour in the day, and thus consisted of 24 levels. However, it was later decided to roll up "`hour_of_day`" into just two periods, each representing half of a 24 hour period, thus representing a "half-day". The column name remained "`hour_of_day`" for ease of use. Here, a value of "1" represents the period 01:00:00 – 12:59:59, and a value of "2" represents the period 13:00:00 – 00:59:59. This split best captures the parts of the day where there is lower crime vs higher crime on average, respectively (see **Figure 4** above for a visualization of this trend). There were two main reasons for choosing this strategy: firstly, it is predicted that this will combat the significant stochasticity present in the hourly data, and therefore lead to increased model accuracy. Secondly, doing so drastically reduces the computational complexity required for analysis, by a factor of roughly 12. One downside to this aggregation method, however, is that it will trade off granularity for the above benefits. On the other hand, it is important to note that the purpose of this study is not to reproduce the most accurate emulation possible of predictive tools used in the real world, but to capture the most important effects – especially those between districts –, and to go on to simulate the future consequences of these effects.

As a result of rolling up hourly data into half-day data, the dataset now consisted of 257,928 observations of count data of mean 15.599 and variance 91.314. These data now represent every possible timepoint at the half-day resolution level for each of the 22 districts for just over 16 years, along with the observed crime count.

2.1.9 Possible Further Detail

Note that an additional feature could have been engineered which would declare whether or not a day falls on the occurrence of a "special event" – this would include not only regularly repeated annual events, but also those which occur irregularly throughout the year. For example, the annual NFL championship Super Bowl match takes place in the US every year on the second Sunday in February (since 2022; before this, the date has changed several times) (Wilner, 2021). There is evidence that the occurrence of a sporting event can affect crime rates in Chicago, particularly when a Chicago sports team is partaking in the event. Observations suggest a potential increase in crime just preceding and just following events, with a potential decrease in crime over the actual duration of the event (Lacqueur & Copus, 2018). A significant type of event specific to Chicago can be found in matches of the Chicago Bulls NBA team, especially if the match is an NBA playoff match. Additionally, this new feature could account for irregularly repeating public holidays such as Thanksgiving, which takes place on the fourth Thursday in November, and Labor Day, which takes place on the first Monday in September. This feature could either consist of a factor which specifies the particular event, or simply a binary one which states "True" or "False" with regard to the day being considered a "special event" day. This could be implemented given more time and resources; given the scope, however, of this particular project, creating such a feature is not entirely necessary, particularly because model accuracy here is not as important, so long as the trend in crime reports between districts is captured.

2.2 Constructing the Predictive Model

Having converted the complex dataset into count data alongside the desired variables for model construction, several different models were considered. In the following, the justifications are set out for choosing the models to be investigated, as well as the methods used to validate each in their predictive performance. Based on the results of this, we will go on to select the best model for use in simulations.

2.2.1 Poisson and Negative Binomial Regression

As the data collected here are count data, they likely do not follow a uniform distribution. This was confirmed by constructing a Q-Q plot of "`crime_count`" values (see **Appendix 3**). Therefore, the dataset doesn't meet the required assumptions for a Multiple Linear Regression (MLR) model.

Typically used with count data is the Poisson regression model. This will be constructed by using the "`glm()`" function in R, specifying "`poisson`" within the "`family`" argument. As with any statistical model, Poisson regression comes with a set of certain assumptions. Presented here are the key assumptions associated with Poisson regression, along with comments on how they apply to our dataset:

1. *Data can be described as following a Poisson distribution* (see **Figure 9** below).
2. *Observations are independent.*
3. *Relationship between predictors and response variable is linear.* This is irrelevant for our data as all predictors are categorical in nature.
4. *No perfect collinearity.* Here, "`month`" and "`date`", naturally, display perfect collinearity (Cramer's V = 1); only one of these will, therefore, be included in the model. This will be decided by the results of model analysis and comparison.

5. *Exogeneity of predictors.* This obviously holds, given the determinate nature of the predictor variables used here.
6. *Large sample size.*
7. *No outliers or anomalies.*
8. *Homogeneity of Variance.* Overdispersion, where the variance is larger than expected, can lead to reduced goodness-of-fit. This is addressed below in the context of Negative Binomial regression.

Our dataset seems to reasonably meet all of these assumptions, except for that of Homogeneity of Variance. This comes as, in a dataset which perfectly follows a Poisson distribution, the mean and variance are equal, and overdispersion is observed when the sample variance is larger than the mean. Here, the mean is 15.599 and the variance is 91.314, giving a dispersion parameter ($\theta = \sigma^2 / \mu$) of 5.854 – in a perfect Poisson distribution this parameter should be 1. This non-homogeneity in variance can be visualized in the Deviance-Residual plot shown in **Appendix 3**.

Thus, to account for over-dispersed data, a Negative Binomial Regression model will be constructed. The Negative Binomial distribution represents a generalization of the Poisson distribution which introduces an additional parameter (dispersion parameter, θ) to account for the overdispersion. Therefore, a Negative Binomial model has the same assumptions as a Poisson model, except for that of Homogeneity of Variance. Here, the Negative Binomial regression model will be constructed using the "`glm.nb()`" function of the "`MASS`" R package.

Both Poisson and Negative Binomial regression can be described by the following formula **(Equation 1)**:

Equation 1. Formula for Poisson and Negative Binomial regression.

$$\mathbf{Log}(\boldsymbol{\mu}) = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 x_1} + \boldsymbol{\beta_2 x_2} + \ldots + \boldsymbol{\beta_p x_p}$$

Where:

- ***log(μ)*** *represents the logarithm of the expected count or rate parameter.*
- $\boldsymbol{\beta_0, \beta_1, \beta_2, \ldots, \beta_p}$ *are the coefficients of the predictor variables.*
- $\boldsymbol{x_1, x_2, \ldots, x_p}$ *are the predictor variables.*

In order to evaluate which distribution best describes the data, a histogram of "`crime_count`" was constructed, and overlayed were the respective probability mass functions (PMFs) of a Poisson distribution where $\mu = 15.599$, and a Negative Binomial distribution where $\mu = 15.599$ and $\theta = 5.854$. We can see the respective fits of these distributions on the data in **Figure 9** below:

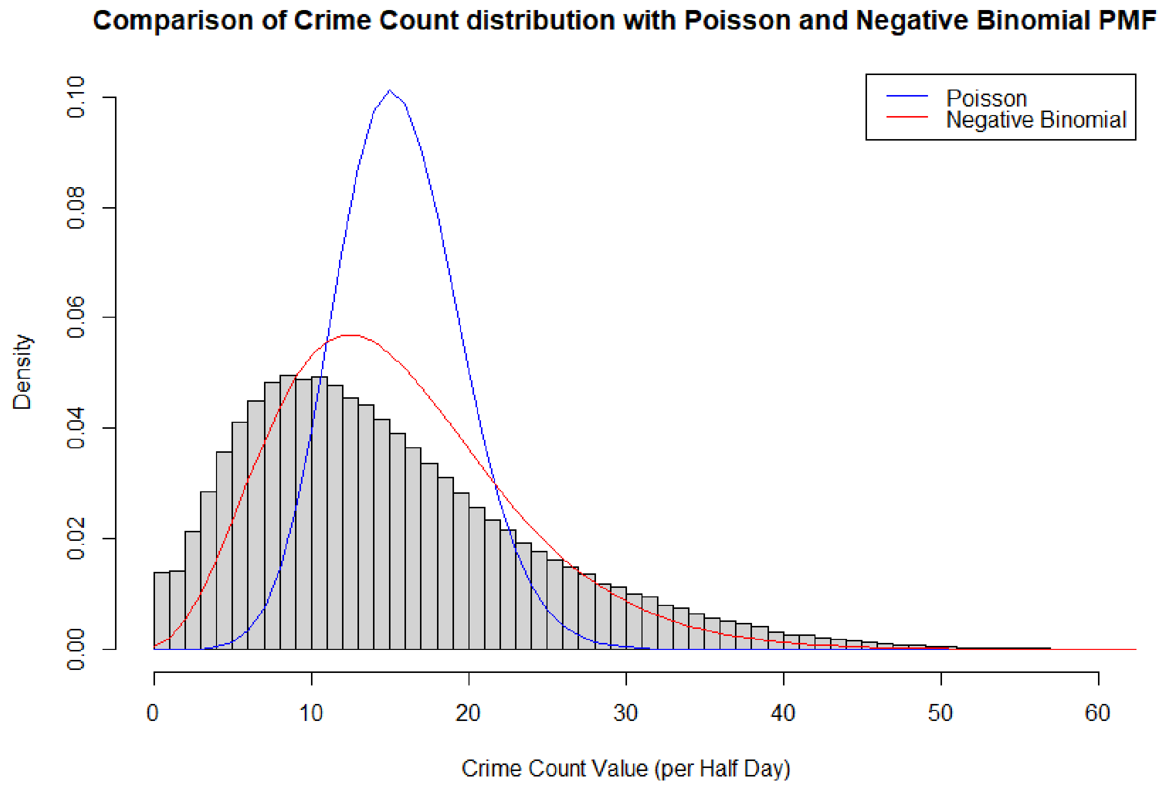


Figure 9. Comparison of Crime Count Distribution with Poisson and Negative Binomial PMF. Here we can see that the Negative Binomial regression model might offer a better fit to the data than Poisson regression.

It is evident that the Negative Binomial distribution might offer a better fit to the dataset, likely due to its taking into account of the overdispersion present in the data. This will be further investigated later in the results section.

2.2.2 Accounting for Zero-inflation

As we can also see in **Figure 9**, the count data may exhibit more zeros than expected under the Poisson distribution assumption, indicating the presence of zero-inflation. To attempt to account for any zero-inflation within the dataset, two different "zero-inflation" models will be constructed: Zero-inflated Poisson Regression (ZIP), and Zero-inflated Negative Binomial Regression (ZINB). These are both constructed using the "`zeroinfl()`" R function from the "`pscl`" package, and represent extensions of the two original models described above. These zero-inflated models account for the excessive zeros by modelling two separate processes: one that generates zeros more frequently (the excess zeros) and another that generates the non-zero counts. Such models typically utilize logistic regression to estimate the probability of a count being zero. Following this, the count data is modelled using the relevant distribution. It is proposed that these zero-inflated models will give better predictive performance if the presence of zeros is greater than that expected by the relevant distribution (Poisson or Negative Binomial) alone, as this indicates the presence of a separate process responsible for determining whether a count is zero or non-zero. To test this hypothesis, a Vuong test will be carried out to test whether each standard or zero-inflated model provides better predictive performance.

2.2.3 Choosing the Best Model

Best-subset selection (BSS) analysis will be carried out for the four proposed models. BSS can help identify the combination of variables to include in a model so as to maximise the trade-off between model complexity and predictive accuracy. The "`bestglm()`" R function was used with the "`family`" argument specified as "`poisson`" and "`negative.binomial`" to generate results for the Poisson and the Negative Binomial model, respectively. However, there do not yet exist functionalities to carry out BSS for ZIP or ZINB models – therefore, the same subset will be used as suggested by BSS within the respective base models. In all BSS analyses, forward stepwise selection will be employed (due to the high computational complexity required to carry out an exhaustive search), and suitability based on AIC.

Note that "`year`" will not be included in the models, as it would not be possible to extrapolate using new year values. While year has an effect on crime rate (see **Figure 8** above), the output of our model needs only to give an output describing the relative likelihoods of crime occurrence between districts; this does not have to be an absolute value, and can therefore be informative in the absence of year data – here, the assumption is being made that any effect that year has on crime rate is distributed equally between districts.

2.3 Simulations

The chosen predictive model was then used as the basis for simulating crime report counts over the course of several years. This process, as well as its justifications, are detailed in the sections below.

2.3.1 Using Crime Count Over Crime Rate

Crime count was used for simulations as opposed to crime count per capita, as this would likely be the metric output by real-life algorithms, and the one read off by police departments in order to assess how to best distribute officers. Utilizing crime rate would only lead to the extra unnecessary calculation to factor in the population of each area. Further justification for this comes in the fact that as population size increases, crime rate decreases, presumably due to lower officer-to-civilian ratio (because of limited resourcing) (see **Figure 10** below).

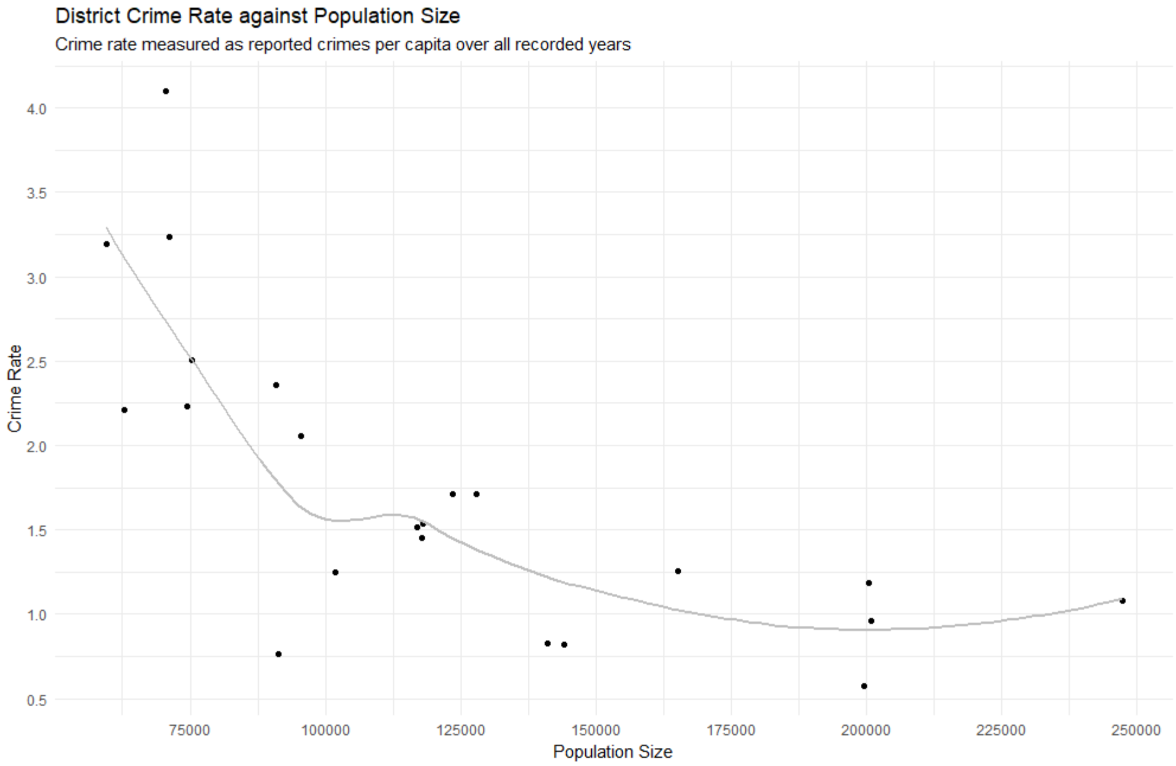


Figure 10. District Crime Rate against Population Size, for all years studied (2001 – 2017).

This effect seems to cancel out broadly the effect that population size would have on crime count (Adjusted R-squared = -0.033, P = 0.576) (see **Figure 11** below).

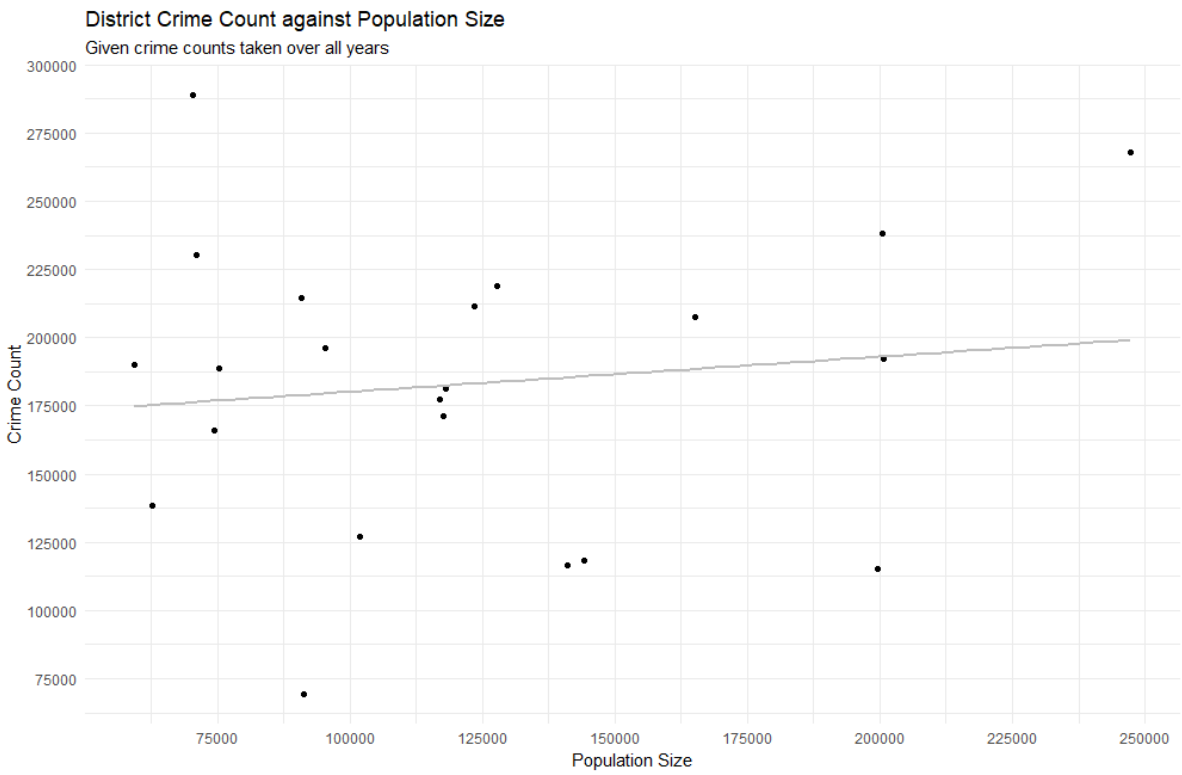


Figure 11. District Total Crime Count against Population Size, for all years studied (2001 – 2017).

However, it must be said acknowledged that these observations are likely conflated by the effect of black population percentage. Upon constructing a MLR model to predict crime count using population size and black population percentage as the predictor variables, the following coefficients were obtained, along with their corresponding p-value:

- Population size = 0.671 ($P < 0.05$)
- Black population percentage = 115,400 ($P < 0.001$)

Therefore, and rather counter-intuitively, a district's crime count is only weakly affected by its population size, and should, therefore, be decided far more strongly by black population percentage.

2.3.2 Simulating Crime Counts

To simulate each year's crime counts (in the absence of any behavioural biases), values were drawn for each possible timepoint at each district from a Poisson distribution (using the "`rpois()`" R function) with lambda set equal to the model's output forecast for the given timepoint and district. All simulated years consisted of 365 days, i.e., leap years were disregarded. Here, we are able to sample from a Poisson distribution because the distribution of crime counts within each specific timepoint and district should be less dispersed than that of crime counts overall, as each repetition is subjected to the same effect of each variable. Thus, we can obtain simulated crime counts by randomly sampling a Poisson distribution, with each "forecast" value as the lambda for each new count. This process is described in **Equation 2** below:

Equation 2. Sampling distribution used for simulated crime counts for a given timepoint and district.

$$\boldsymbol{C_{i(t+1)} \sim Poisson(F)}$$

Where:

$\boldsymbol{F}$ = *Forecast*

$\boldsymbol{C_{i\,(t+1)}}$ = *Simulated crime count*

For proof of concept comparisons, see **Appendix 6** for proof that a Poisson distribution is more suitable that a Negative Binomial distribution for modelling crime count distribution for a given month, half-day, and district (for the purpose of sampling during simulations), as well as a comparison of similarity between the training dataset crime count distribution and a simulated year crime count distribution.

2.3.3 Simulating the Effect of Overcompensation

To take into account the behavioural bias of overcompensation, a parameter, "α" (alpha), was established. This can be set at different levels to test the effects of different degrees of overcompensation. In order to emulate this behavioural bias, a new, "biased" forecast is formulated for each timepoint and district, according to the following formula (**Equation 3**):

Equation 3. Formula for biased forecast considering overcompensation.

$$\boldsymbol{F_b = F_i + (F_i - \bar{F}) \cdot \alpha}$$

Where:

> $\boldsymbol{F_b}$ = *Biased forecast*
> $\boldsymbol{F_i}$ = *Forecast at given iterable*
> $\boldsymbol{\bar{F}}$ = *Forecast mean at timepoint between districts*
> $\boldsymbol{\alpha}$ = *Overcompensation parameter*

This biased forecast represents the effective mean of the predicted crime count, given police officers' assumed behavioural bias. The simulated new crime count will then be based off of this biased forecast, where it will represent the new "lambda" value in the Poisson distribution sampling function outlined above (where "Biased Forecast" ≤ 0, "Biased Forecast" was set to 0.1 to avoid "NA" values being returned by the "`rpois()`" function). Thus, α may be interpreted as the coefficient by which extra resources will be sent to a district for every count that the forecast is above the average between districts (and vice-versa for districts below the average). For example, if the forecasted crime count for a given district at a certain timepoint is 15, and the average between districts is 10, for an α value of 0.2, there will be an extra investment equivalent to 1 extra effective forecasted crime $\left((15 - 10) \cdot 0.2\right)$ into this district. Note that here there is an assumption being made that each added officer or unit resource results in an equal increase in crimes reported. For example, it is assumed that adding an officer to a district with x officers already present will lead to the same average increase in reported crimes as with adding an officer to a district with $2x$ officers present. Thus, the process of sampling these now biased counts can be described by **Equation 4** below:

Equation 4. Sampling distribution used for simulated crime counts for a given timepoint and district, given the effect of human bias.

$$\boldsymbol{C_{i(t+1)} \sim Poisson(F_b)}$$

Where:

> $\boldsymbol{F_b}$ = *Biased Forecast*
> $\boldsymbol{C_{i\,(t+1)}}$ = *Simulated crime count*

The new simulated crime counts are then added back into the dataset. With the dataset updated with new data, the model is retrained, utilising this new dataset.

Note that for later generations, the model encountered convergence issues – this was ameliorated by increasing the maximum number of iterations within the optimization function (from the default of 25 to 100, using the "`glm.control()`" argument within the "`glm.nb()`" function), to allow for full convergence.

Note that another algorithm to simulate behavioural bias was initially investigated: a z-score was assigned to each forecasted crime count value, in relation to the same values of the other districts at the same timepoint. This z-score was then combined with the constant α to modulate the forecast for each timepoint and district (see **Appendix 7** for proof that crime count by district follows a normal distribution, as is assumed for the derivation of z-scores). However, this resulted in fluctuations in the total crime count per year – this likely represents a violation of the assumption of fixed police resources. This is because, whilst the difference between forecast and mean forecast for each district at the same timepoint balances out, z-scores don't necessarily do so. Thus, the sum of biased forecasts over all timepoints and districts could deviate from the original forecasts for a year.

2.3.4 Simulating the Effect of Overcompensation Plus Confirmation Bias

Additionally, simulations were carried out to model the effect of confirmation bias in this system. This effect is simulated in compound with overcompensation and represents the occurrence of confirmation bias as a result of changing crime rates due to overcompensation. Here, confirmation bias is modelled as the percentage change in crime count between the previous year and the current year, and is modulated by a new parameter, "β" (beta). Thus, a new biased forecast is formulated for each timepoint and district, according to the following formula:

Equation 4. Formula for biased forecast which incorporates both overcompensation and confirmation bias.

$$\boldsymbol{F_b = F_i + (F_i - \overline{F}) \cdot \alpha + \left(\frac{C_t - C_{t-1}}{C_{t-1}}\right) \cdot \beta}$$

Where:

$\boldsymbol{F_b}$ = *Biased forecast*
$\boldsymbol{F_i}$ = *Forecast at given iterable*
$\boldsymbol{\overline{F}}$ = *Forecast mean at timepoint between districts*
$\boldsymbol{\alpha}$ = *Overcompensation parameter*
$\boldsymbol{C_t}$ = *Total district crime count of current year*
$\boldsymbol{C_{t-1}}$ = *Total district crime count of previous year*
$\boldsymbol{\beta}$ = *Confirmation bias parameter*

Thus, β may be interpreted as the coefficient by which extra resources will be sent to a district as a percentage of the difference in district total crime count between the previous year and the current year (and vice-versa for where there is a negative difference between years). Crime counts are again sampled using the biased forecast as in **Equation 4**.

2.3.5 Null Simulation

A null simulation was carried out wherein both α and β were set to zero. This was done to confirm the validity of both model construction and simulations in replicating crime counts, and is expected to match broadly the distribution of mean crime counts between districts across the years studied.

2.3.6 Instituting a Rolling Window

The proposed method for applying a rolling window between simulations was initially to remove the oldest year's data during dataset update, and to add the new, simulated year's data. However, it is not possible to remove the oldest year as – in the absence of any bias effects – this would lower the new mean of the new training set, due to the fact that crime reports decrease on average with year. This would then result in simulations with lower mean crime counts than the previous mean. Therefore, as a workaround, the oldest year is retained, while the new year's data is still added. However, each new year is weighted twice that of the previous year when training the predictive model in order to offset the dilution effect of adding another year for every iteration of the simulation. This is achieved by assigning each new year the necessary weight (a numeric value in a column named "`weights`") during dataset update, before using the "`weights`" argument within the "`glm()`" R function during model training.

As briefly mentioned, we used the geometric sequence $a_n = a_1 \cdot 2^{n-1}$ (also known as a doubling sequence) to derive the weightings used in emulating a rolling window. As a result, each new year has the same weight as the sum of all preceding years. This results in an effective two-year window, as the sum of this geometric series comes to 2 (one fully weighted year, plus a half-weighted previous year, plus a quarter-weighted previous year, and so on). Five years (2012 – 2016) were taken from the original dataset to build this new model; weighting values of 1 were added to these five years. Then, new weighting values (following the aforementioned doubling sequence) were added to each new year as detailed above.

Ultimately, both a full model, initially trained on all years (2001 – 2017), and a rolling window model, initially trained on just five years (2012 – 2017) will be constructed and used for simulations.

2.3.7 Summary of Functions Defined for Simulations

Below in **Figure 12** is a list of the main functions defined in R for use in simulating future crime patterns.

```r
# Creating data frame of all time points in a year (picked 2015 as it's not a leap-year)
timepoints <- chic[chic$year == 2015, ][-c(2,7)]


# Getting regular forecast
get_model_forecast <- function(model){...}


# Getting biased forecast, just overcompensation
get_biased_forecast <- function(model, alpha){...}


# Getting biased forecast, with confirmation bias included
get_biased_forecast_with_conf_bias <- function(model, alpha, previous_dataset, current_dataset, beta){...}


# Getting biased new crime count, just overcompensation
get_new_crime_count <- function(model, alpha, data){...}


# Getting biased new crime count, with confirmation bias included
get_new_crime_count_with_conf_bias <- function(model, alpha, previous_dataset, current_dataset, beta){...}


# Function to add new crime data to training dataset, no rolling window
update_dataset <- function(new_crime_data, current_dataset){...}


# Function to add new crime data to training dataset, with effective two-year rolling window
update_dataset_rolling_two <- function(new_crime_data, current_dataset){...}


# Function to add new crime data to training dataset and retrain model
update_model_without_weights <- function(updated_dataset){...}


# Function to add new crime data to training dataset and retrain model
update_model <- function(updated_dataset){...}
```

Figure 12. List of main functions defined in R for use in simulations.

2.3.8 Proof-of-concept Simulations

Two proof-of-concept experiments were also carried out to prove the validity of the approach used here, in the absence of any other real-world effects in the data (one for overcompensation, and one for overcompensation plus confirmation bias; effective two-year rolling windows were used for both experiments). To do this, we replaced the actual crime report count data with counts randomly sampled from Poisson distributions, where λ of each distribution is randomly generated for each district, giving different mean crime report rates across the districts. Thus, the only signal observed should be that from the difference in crime report rates between districts.

2.3.9 Visualization

Finally, the results of the simulations of overcompensation plus confirmation bias were converted into a spatiotemporal visualization, using the shapefile of current Chicago police districts taken from https://data.cityofchicago.org/Public-Safety/Boundaries-Police-Districts-current-/fthy-xz3r. These are shown alongside a map of Chicago police districts by Black population percentage, so that the effects of worsening racial bias can be properly visualized.

3 Results

3.1 Model Results

3.1.1 Best-subset Selection

Given that all variables investigated evidently display significant effects on crime count, the best subset for both Poisson and Negative Binomial models is likely to be most, if not all, variables. Nonetheless, BSS was carried out to determine quantitatively the best subset. BSS outcomes for both models were the same, with the crucial result of "`date`" being included and not "`month`" (see **Appendix 5** for R output of Negative Binomial regression model BSS analysis). "`month`" was likely excluded due to collinearity with "`date`" (Cramer's V = 1); adding in "`month`" doesn't add much or any additional information, and so it is redundant from the best-performing model. "`date`" predicts better than "`month`" due to the increased granularity that the former gives, which ultimately decreases predictive error. Other than "`month`", all other variables were included in the best subset, for both types of model. Again, this is unsurprising given the findings in the exploratory data analysis – all factors appear to have a significant effect on crime count. Looking at the results of the Negative Binomial BSS analysis, "`hour_of_day`" demonstrates the highest impact on crime count ($F = 144{,}340.47$, $P < 0.001$), followed by "`district`" ($F = 5496.53$, $P < 0.001$). "`day_of_week`" and "`date`" ($F = 257.44$, $P < 0.001$; $F = 52.98$, $P < 0.001$, respectively), too, showed highly significant effects on crime count, albeit with somewhat lower F-values. Upon initial inspection, "`day_of_week`" appeared to have a comparably weak, albeit robust, effect on crime count, therefore this result aligns with initial findings. However, the effect of "`date`" on crime count was shown in the exploratory data analysis to be fairly strong. The reason that this is not fully reflected in the F-value obtained is that the variable has far more degrees of freedom ($df = 365$) than the other variables, given that it has 366 levels. This effect – known as the "Many Levels Problem" – results in a lowered F-value, as the variance within levels becomes magnified, compared to the variance between levels. A solution to this problem can be found in reducing cardinality by grouping levels to a meaningful level. Therefore, it was decided to continue model building using the "`month`" variable, as opposed to "`date`". As well as returning a higher F-value, this strategy will also drastically reduce computational complexity during model construction and simulation. Once more, as effects are being assumed as equal across districts, timepoint granularity isn't of overwhelming priority for the purposes of this study; the main aim of the model is to capture how the effect on crime count differs between districts. Thus, it is prudent that computational complexity is optimised in preference of maximising granularity. To make up somewhat for lost granularity, one could, as previously mentioned, include a "special event" feature to inform the model of certain days which might influence crime rates. This would address problems such as the occurrence of Halloween – "October" relates to an average of all days in the month, so the model might underestimate crime rate on days when crime spikes around Halloween, and slightly overestimate it on other days in October. However, this difference would be accounted for by the aforementioned new feature.

Note that significant effect likely from year – again, this will be left out in real-life because will be predicting in present-time, not on historical data, and predicted likelihoods will be interpreted relative to each other; therefore, the effect of year is assumed to affect all districts equally. However, another Negative Binomial regression model was built to prove how much of an effect year has on predicted crime count, and a brief investigation of fit was made. Here, AIC = 1,539,719, compared to the original model's value of AIC = 1,630,719. Compared to the actual model used, this represents a significant increase in accuracy – therefore, we know that this is a large contributor to crime count. Thus, our model accuracy is an underestimate of that if it were to be used in the real world; taking predicted crime counts relative to one another would show even more accuracy than implied by the several goodness-of-fit measures calculated for our model here.

3.1.2 Vuong Test for Zero-inflated Models

In order to determine whether the zero-inflated models performed better than the standard base models, Vuong Tests were carried out, using the subset of variables mentioned above. The zero-inflated versions were found to offer little improvement over the base models. Vuong test showed there to be a statistically significant difference between predictive performance in base model and zero-inflated model for both Poisson and NegBin ($P < 0.001$). However, looking at the AIC values between base and zero-inflated models, the difference, while significant, is rather weak (Poisson AIC = 1,778,500 vs ZIP AIC = 1,760,459; Negative Binomial AIC = 1,630,719 vs ZINB AIC = 1,623,142). For pragmatic reasons, we chose to only consider the base models from here on in for use in simulations. This comes because, despite the slight increase in performance, the zero-inflated models take far longer to train. Given the nature of the simulations to be run, this would cost too much time to be worth the relatively minor payoff, especially considering the fact that optimising predictive accuracy is not the key aim of this study, so long as the key effects to be studied are successfully emulated. This relatively minor improvement likely comes from the fact that excess zeros are not generated by separate process as much – the reason we see a large number of zeros is simply because λ is close to zero.

3.1.3 Comparing Poisson vs Negative Binomial Model Performance

Having come to a conclusion as to which variables to include and having narrowed down which model to use to just two (standard Poisson and Negative Binomial regression), an investigative comparison was made between the two candidate models. Given below in **Table 1** are the key results obtained during model validation:

	Model	
Validation Measure	Poisson Regression	Negative Binomial Regression
AIC	1,778,500	1,630,719
BIC	1,778,918	1,631,148
Deviance	648,616	275,577
Null Deviance	1,454,850	600,481
Deviance Ratio	0.554	0.459

Table 1. Key validation measures for comparison of Poisson and Negative Binomial regression model performance.

All of the tested validation measures were lower (and therefore better) for Negative Binomial regression. There is a stark difference between the deviances of the two models. A chi-square test on the deviances of the two models confirmed there to be a significant difference ($\chi^2 = 610.77$, $p < 0.001$). We can see that the null deviances, too, differ greatly. This constitutes evidence that a Negative Binomial distribution better describes the count data than a Poisson distribution. Negative Binomial regression also displays a lower deviance ratio compared to Poisson regression. This means that the former performs even better compared to its null model than the latter does.

The difference in predictive performance between the two models can be visualised by constructing a goodness-of-fit graph for both models, as is shown below in **Figure 13**.

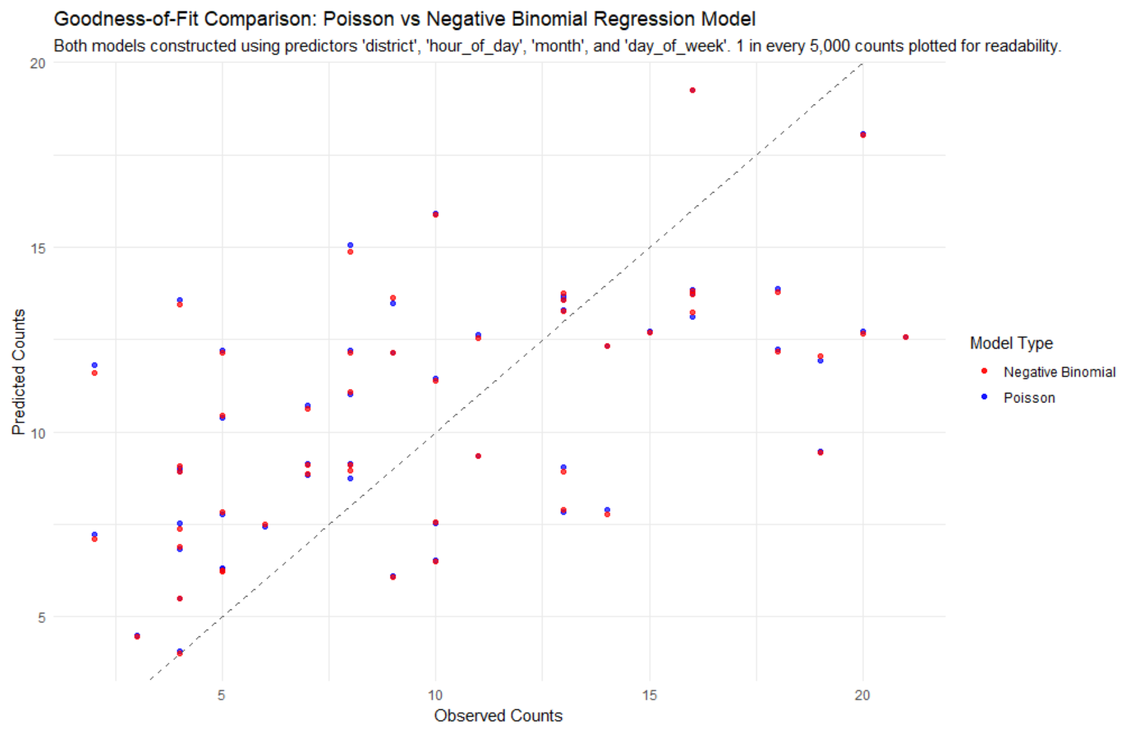


Figure 13. Goodness-of-Fit Comparison: Poisson vs Negative Binomial Regression Model. Both models constructed using predictors "`district`", "`hour_of_day`", "`month`", and "`day_of_week`". 1 in every 5,000 counts plotted for readability. The closer each point is to the line of best fit represents how much better the prediction is.

Shown below in **Figure 14** is the goodness-of-fit graph for the Negative Binomial model, with all counts (except for four outliers) shown. As can be seen, the model displays a certain degree of predictive power. However, it is evidently somewhat limited. Reasons for this are discussed later in **Section 4.1**.

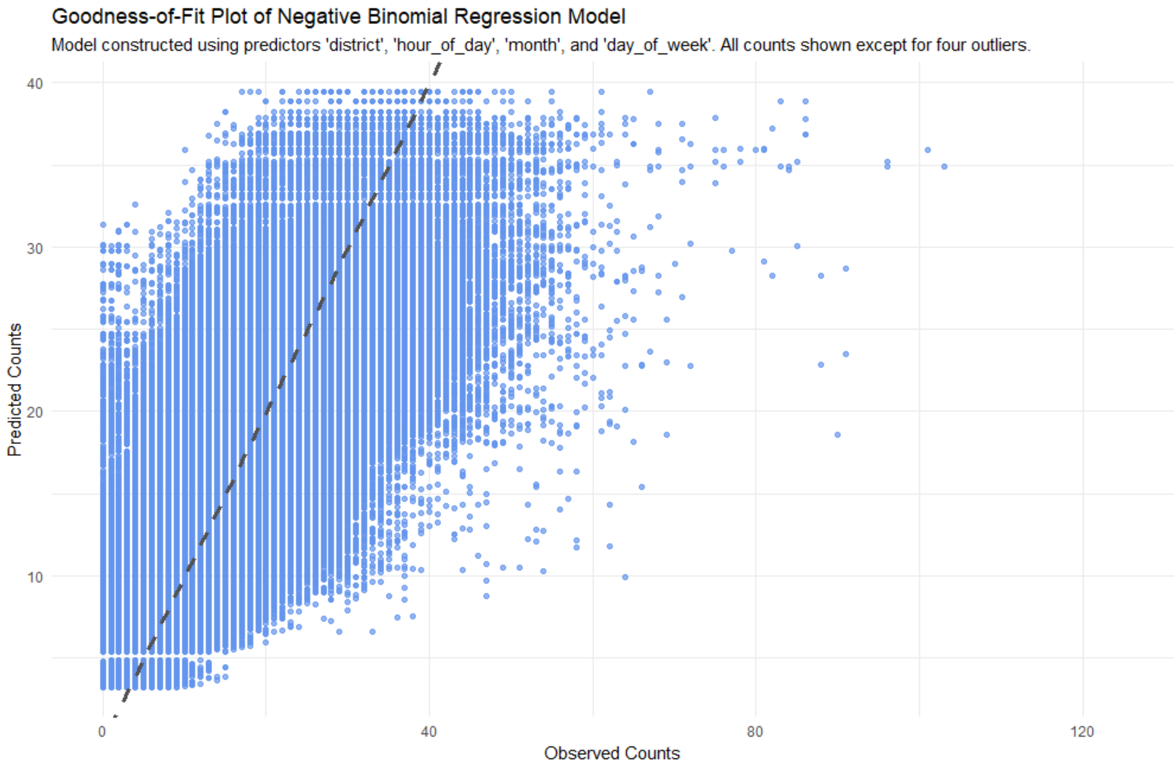


Figure 14. Goodness-of-Fit Plot of Negative Binomial Regression Model. Model constructed using predictors "`district`", "`hour_of_day`", "`month`", and "`day_of_week`". All counts shown except for four outliers.

Based on the above findings, a Negative Binomial regression model will be used for simulations with the following predictor variables included: District, Month, Half-day and Day of Week.

Note also that when training the chosen model on just five years, as was done for the rolling model, AIC and deviance remain roughly proportional to the full model trained on all years studied. What's more, the deviance ratio of the five-year model (0.393) proved significantly better than the full model (0.459).

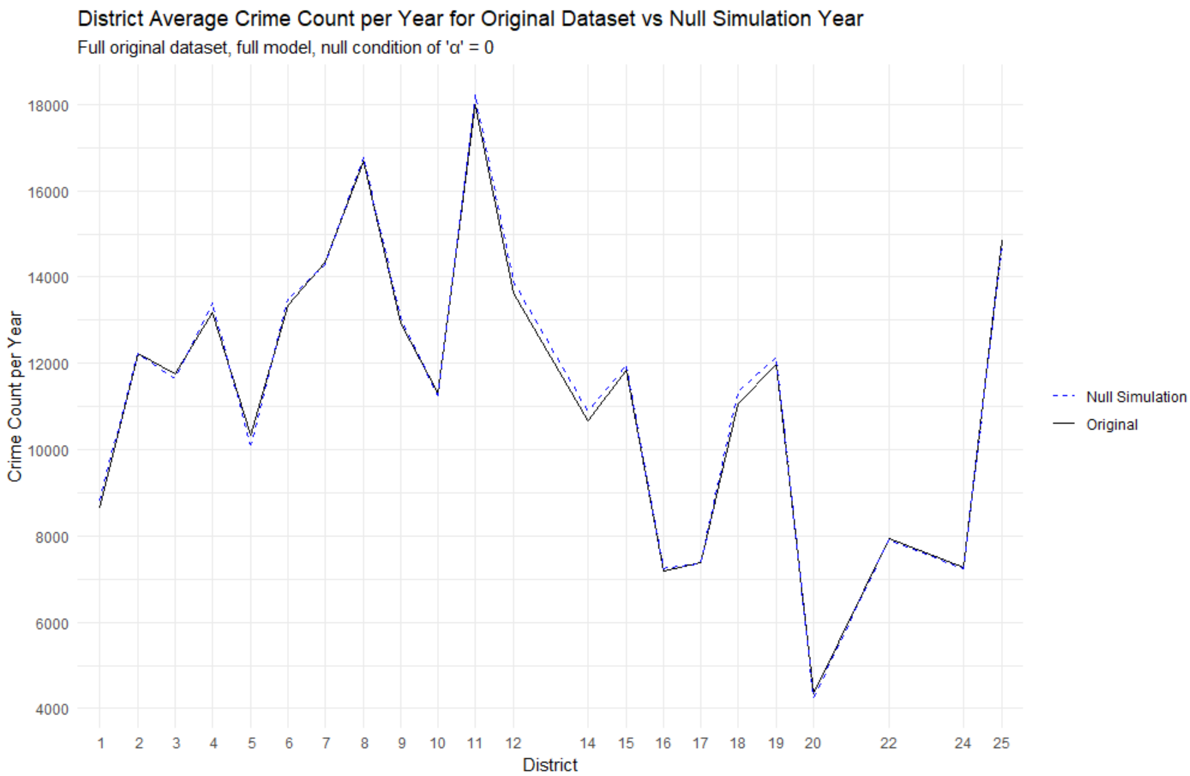
Therefore, taking a five year window doesn't hinder model performance – if anything it improves it. This observation corroborates previous findings in the literature (see **Section 1.4**). This is likely due to reduced year span leading to reduced variability in crime count, given the trend in crime count over the years studied. Once again, accuracy not the prime priority for the purposes of this study, as effects on district crime count will be similar in simulations.

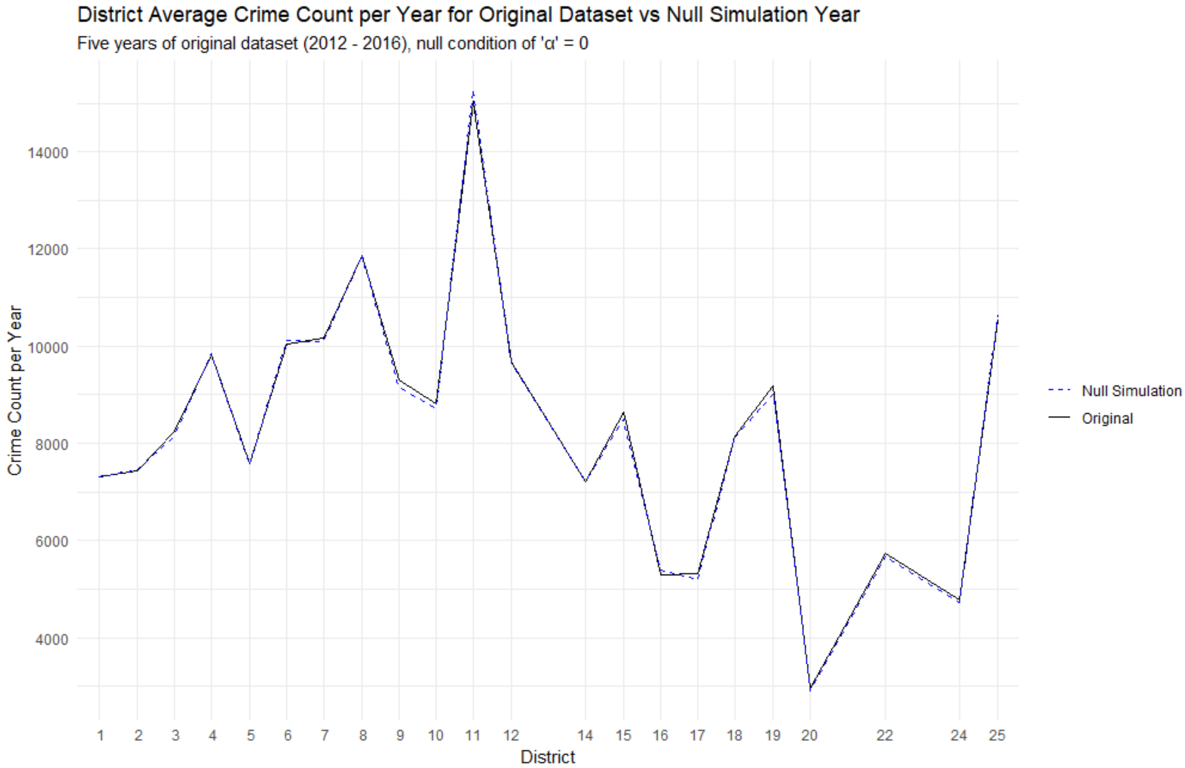
3.2 Simulation Results

3.2.1 Null Simulations

Null simulations (shown below in **Figures 15a & 15b**) demonstrate the validity of the methodology utilized to simulate crime counts of subsequent years. Two null simulations were run – one using the full model trained on all years (2001 – 2017), and one for the rolling window model, which was trained just on five years (2012 – 2016). For both, we expect the crime counts per district of the null simulation to be no different than that of the average crime counts per district per year of the original data, given that the models were trained on these data, and therefore a null simulation in which no additional parameters are set should reflect the mean outcomes of the training dataset. For both experiments, there proved to be no difference between the means of the two datasets ($p > 0.999$, Welch's Two-Sample t-test).

Figures 15a & 15b. District Average Crime Count per Year of Original Dataset vs District Crime Counts within a Null Simulation Year (**Figure 15a** shows full time span and full model; **Figure 15b** shows five-year window and five-year model). Note gaps on the x-axis between missing districts – as a line graph, both variables had to be numeric; R therefore has treated the districts as a numeric series with gaps, coercing a space between some districts. There was no workaround to this in R, and a line graph is the best way to visualize these data – further within our results, there become too many treatments to be legibly represented on, say, a clustered bar chart.





3.2.2 Overcompensation (No Rolling Window)

First tested was the effect of overcompensation on district crime count. This was done for three different levels of α, shown below in **Figure 16**. We see here that all levels of α generally result in an increase in crime count in districts with yearly crime counts above the mean (8313.6 crime reports per year here), and a decrease where yearly crime count is below the mean. Further, all three levels lead to a greater effect as α increases, with α = 0.2 offering the largest effect. Take district 11 for example, where the yearly crime count increases from around 15,000 to around 16,200 due to the effect of overcompensation where α = 0.2.

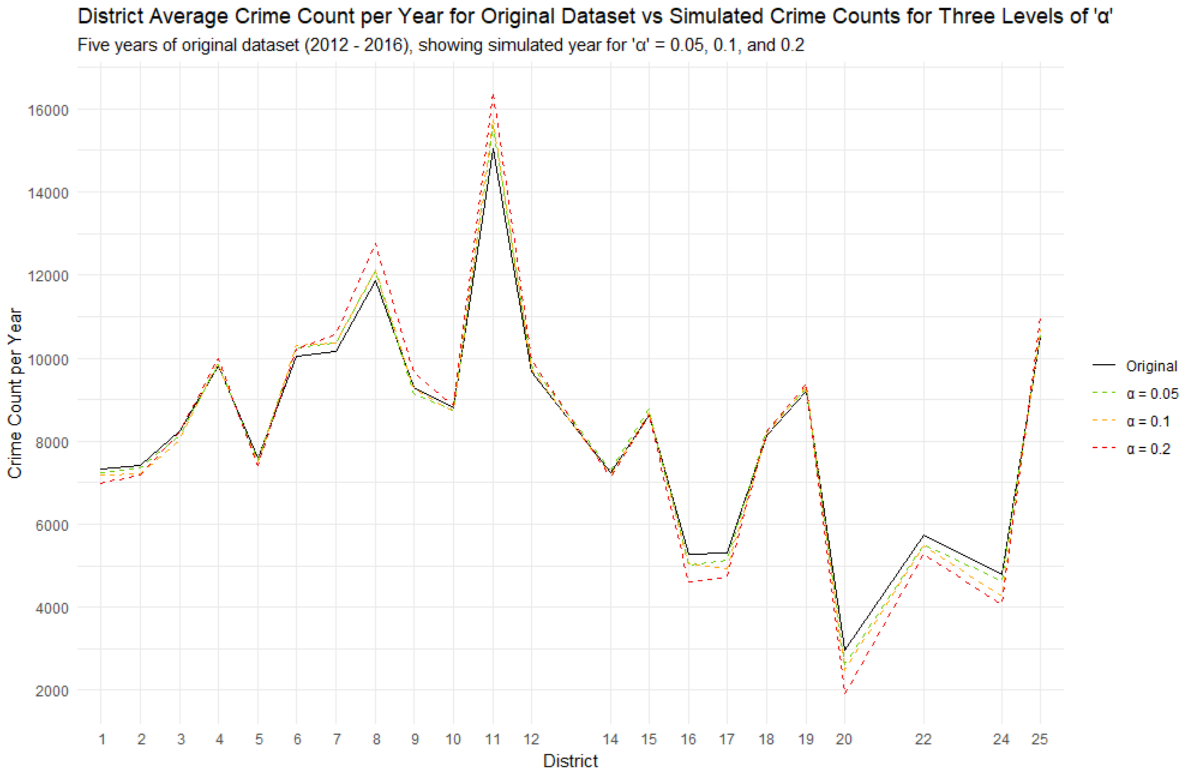


Figure 16. District Average Crime Count per Year for Original Dataset vs Simulated Crime Counts for Three Levels of 'α'. Five years of original dataset (2012 - 2016), showing simulated year for 'α' = 0.05, 0.1, and 0.2.

The effect of overcompensation was then investigated over the course of eight simulated years, given a full model (using all years between 2001 and 2017) with no rolling window, for α = 0.2. The result of this is shown below in **Figure 17**. Here, crime counts are observed to jump up (and equally down) in the first simulated year, however, they do not continue to change over subsequent years, even with α set at 0.2. This is because the new crime data is significantly diluted whenever it gets added into the updated dataset, and, therefore, the next updated model will reflect roughly the mean of all years included in the updated dataset.

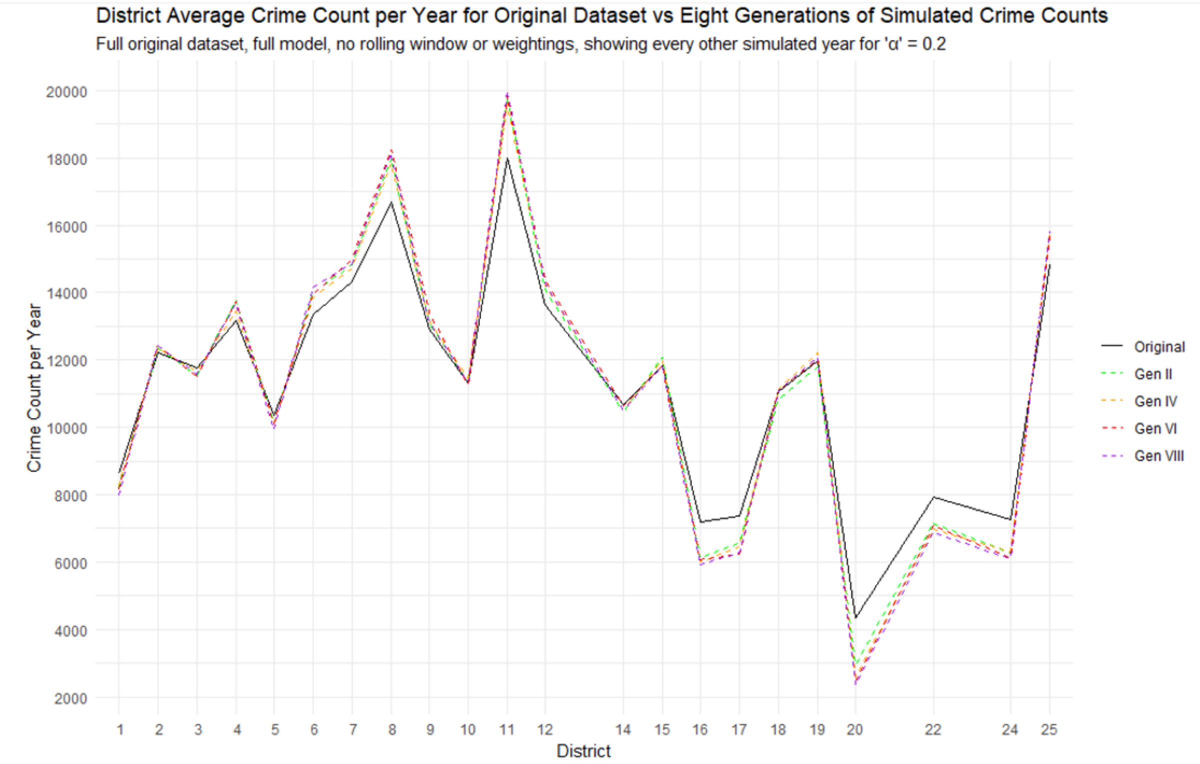


Figure 17. Full window, every other year, no weighting, $\alpha = 0.2$, to show plateau (can't escape stochasticity).

3.2.3 Overcompensation (Effective Two-year Rolling Window)

The effect of overcompensation on district crime count was then investigated with an effective two-year rolling window. Simulations were run for eight years, and for three different levels of α (0.05, 0.1, and 0.2). The results of these three simulations are shown below in **Figures 18a**, **18b**, and **18c**. All three simulations show increasing (and equally decreasing) crime counts in districts across the eight years, with increasing degrees of extremity as α increases. Where α = 0.05, the year-on-year changes appear roughly regular, whereas for α = 0.2, the changes seem to become more drastic for every year. Thus, we can see that once α passes a certain value, the bias enters a runaway feedback loop. Comparing this trend with the same simulation only without a rolling window shows the power that this factor might play in the evolution of racial bias in real-world algorithms.

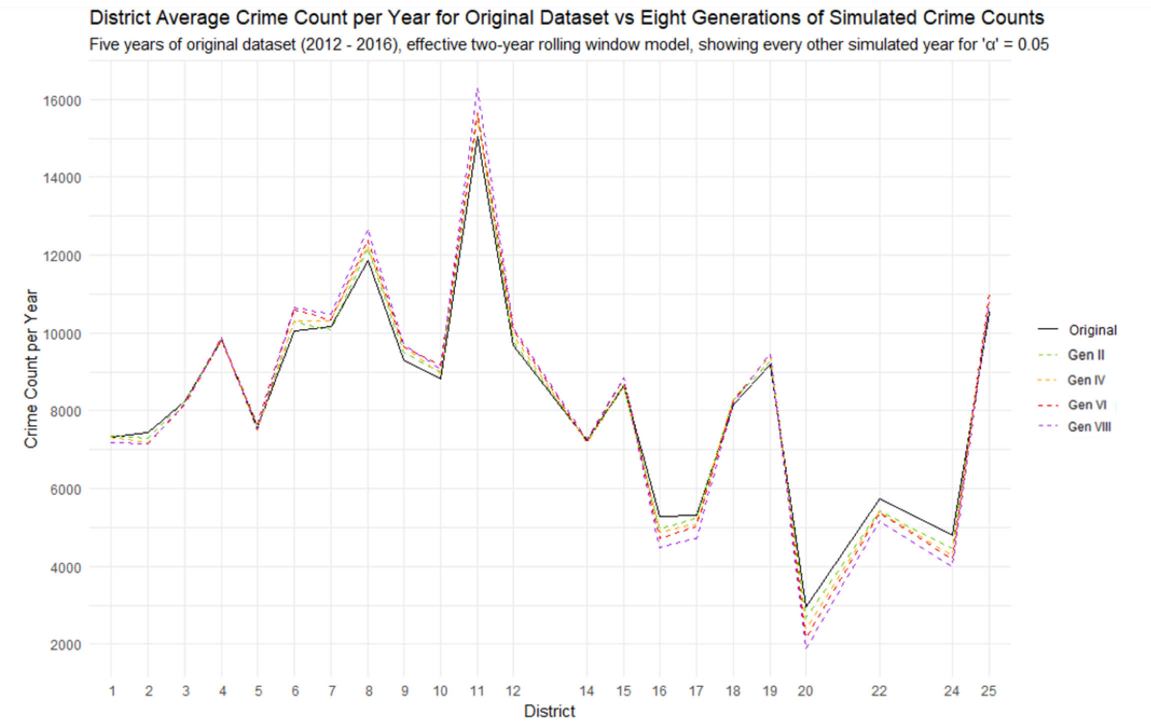


Figure 18a. District Average Crime Count per Year for Original Dataset vs Eight Generations of Simulated Crime Counts – five years of original dataset (2012 - 2016), effective two-year rolling window model, showing every other simulated year for 'α' = 0.05.

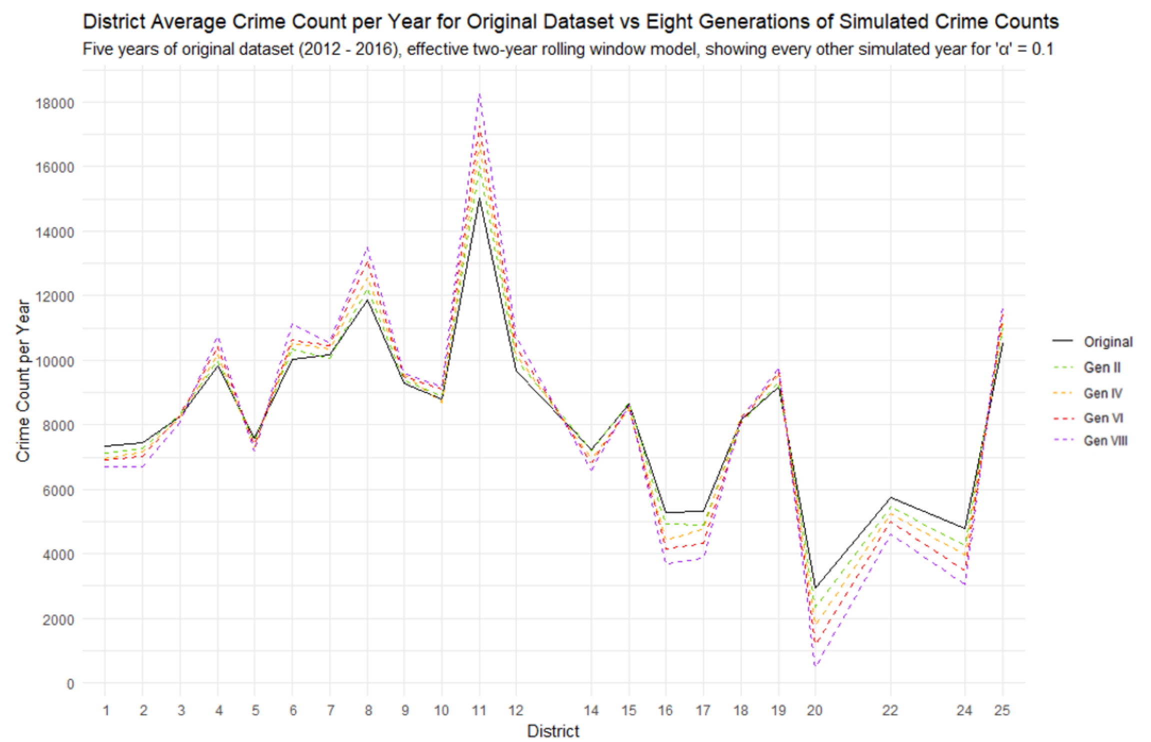


Figure 18b. District Average Crime Count per Year for Original Dataset vs Eight Generations of Simulated Crime Counts – five years of original dataset (2012 - 2016), effective two-year rolling window model, showing every other simulated year for 'α' = 0.1.

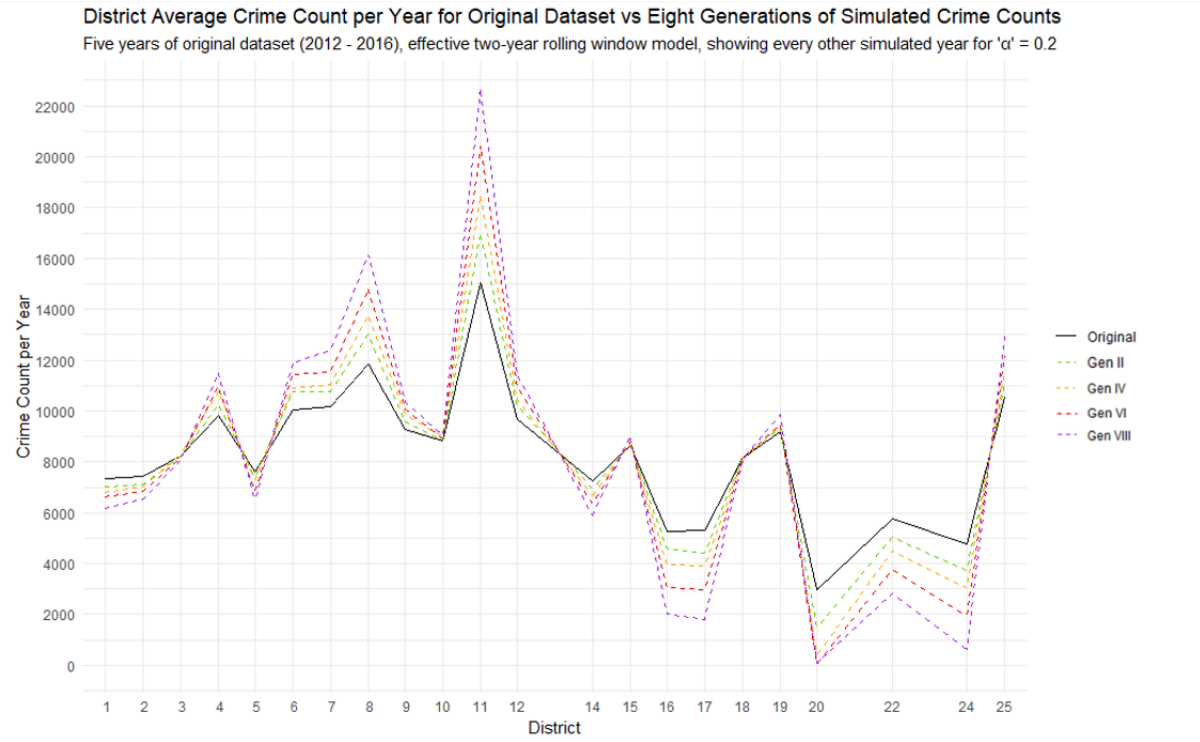


Figure 18c. District Average Crime Count per Year for Original Dataset vs Eight Generations of Simulated Crime Counts – five years of original dataset (2012 - 2016), effective two-year rolling window model, showing every other simulated year for 'α' = 0.2.

3.2.4 Overcompensation Plus Confirmation Bias (Effective Two-year Rolling Window)

Next, the effects of both overcompensation and confirmation bias were investigated. These are shown across three different simulations. All three simulations shown use an effective two-year rolling window, and have α set to a value of 0.1 (this is considered here an intermediate degree of overcompensation).

Figure 19a shows the effect of setting the parameter β to three distinct levels: 0.25, 0.5, and 1. The resulting district crime counts are shown after five years of simulation ("Gen V"), along with the per year average district crime counts of the original dataset (shown in grey), and the "baseline" simulated district crime counts for where β is set to zero (shown in black). Here we see that crime count changes at an increasing rate as β increases. This is not surprising as, representing a percentage change, the confirmation bias component within the simulations will compound with every year. Therefore, the effect on crime count of increasing β is exponential.

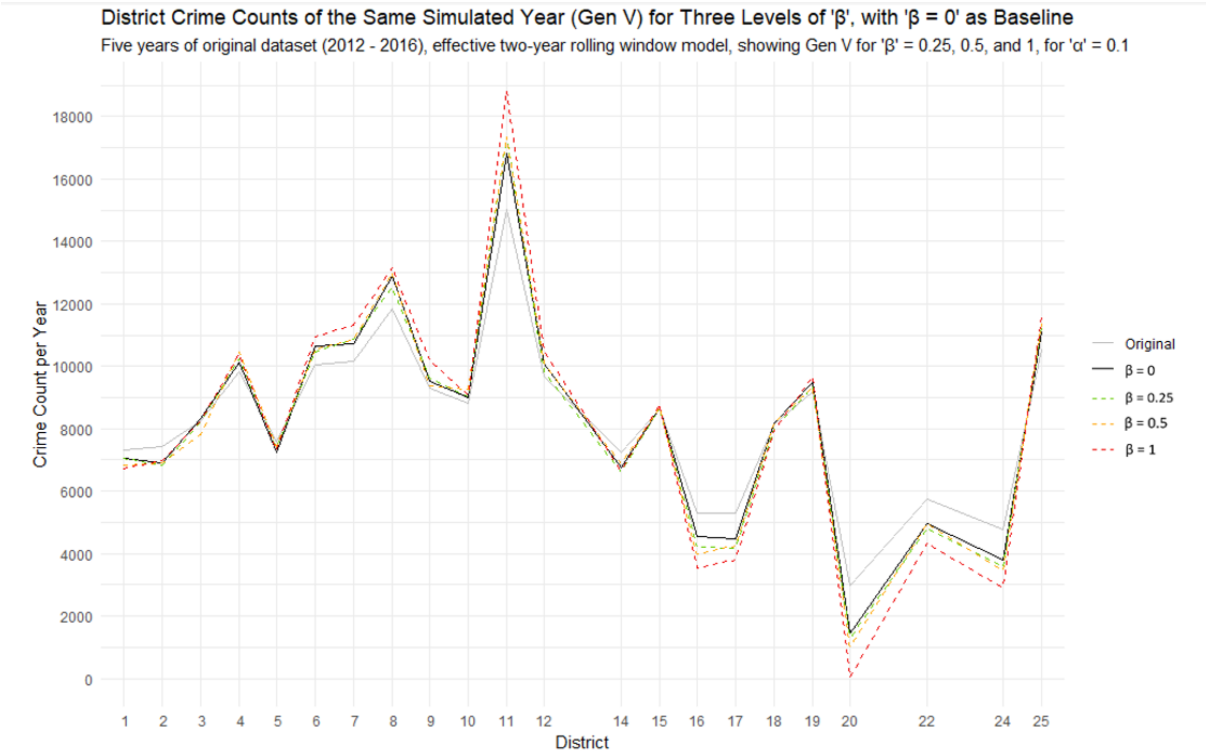


Figure 19a. District Crime Counts of the Same Simulated Year (Gen V) for Three Levels of 'β', with 'β = 0' as Baseline. Five years of original dataset (2012 - 2016), effective two-year rolling window model, showing Gen V for 'β' = 0.25, 0.5, and 1, for 'α' = 0.1.

Shown below by **Figure 19b** is a comparison of the effects on district crime count of just overcompensation vs overcompensation plus confirmation bias, at the second, fifth, and eighth simulated years ("Gen II", "Gen V", and "Gen VIII"). Here we see that the difference between the effects of the two conditions increases as years go on. Once again, this is due to the compounding effect of confirmation bias.

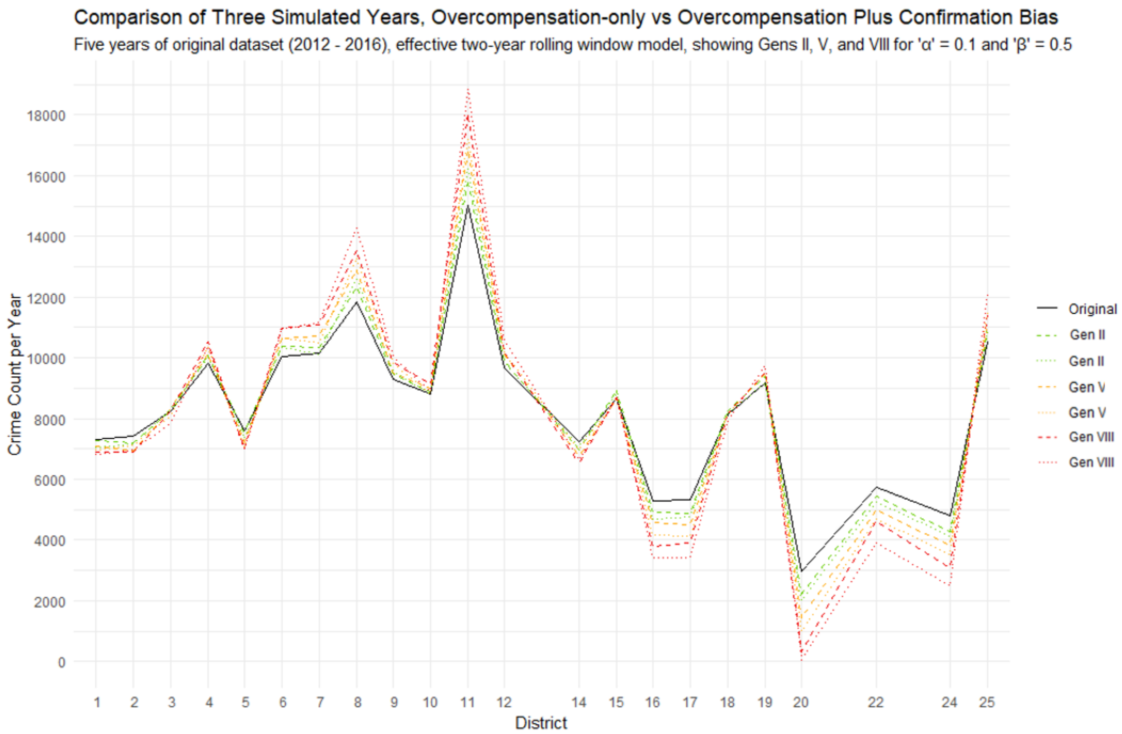


Figure 19b. Comparison of the Same Three Simulated Years, Overcompensation Only vs Overcompensation Plus Confirmation Bias. Five years of original dataset (2012 - 2016), effective two-year rolling window model, showing Gens II, V, and VIII for 'α' = 0.1 and 'β' = 0.5. Here, the dashed lines represent overcompensation only, while the dotted lines represent overcompensation plus confirmation bias.

Finally, in **Figure 19c** we see described the effect on district crime count of overcompensation plus confirmation bias for $\alpha = 0.1$ and $\beta = 0.5$, with an effective two-year rolling window. These specific conditions are shown here as – out of the combination of conditions investigated – they represent what we will term the “best-approximation” case for modelling the degree to which these two biases are present in the real world, as well as the rolling window used. Here, we chose what were considered plausible and intermediate settings.

Profound changes in crime counts were observed in certain districts. For example, in District 11, where Black population percentage is 85.7%, reported crimes increase by roughly 4,000 reports per year after eight years. In contrast, in District 20, where Black population percentage is just 11.2%, reported crimes decrease by 3,000 crime reports per year (in fact, they reach zero). The feedback loop observed here appears to have runaway effects, and these effects are evidently extensive after just eight years of projection.

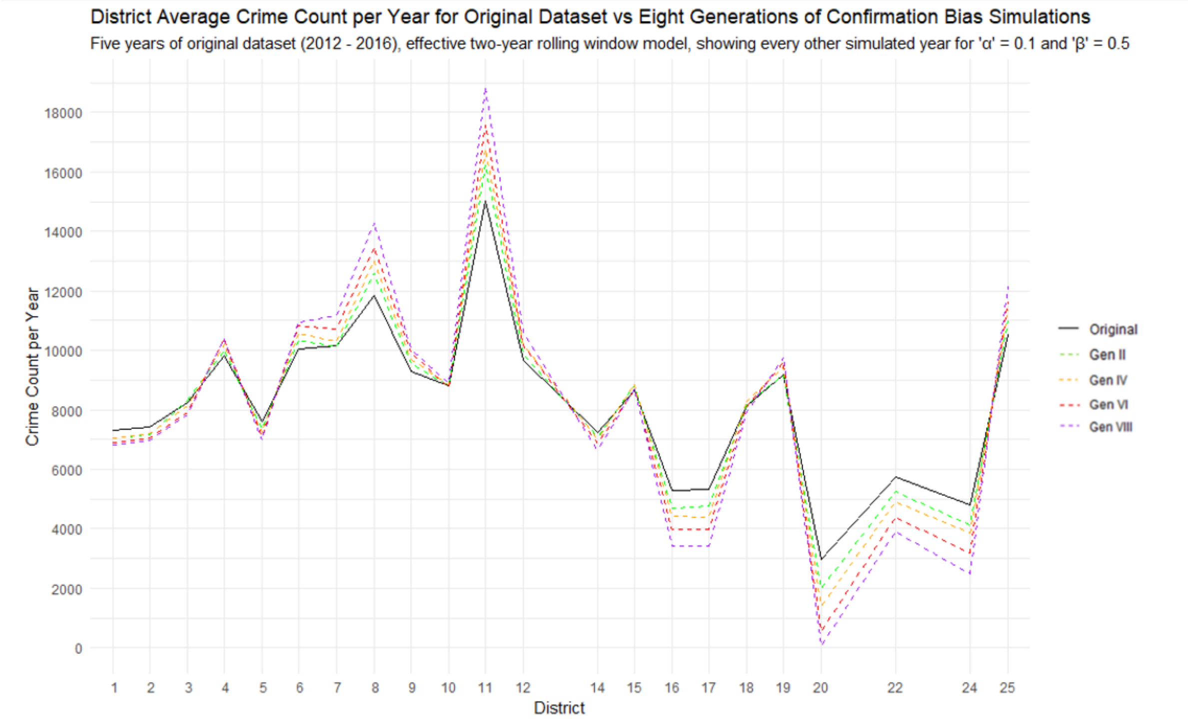


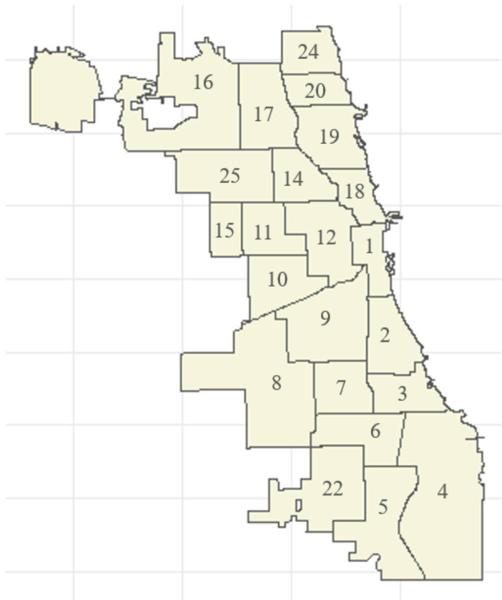
Figure 19c. District Average Crime Count per Year for Original Dataset vs Eight Generations of Confirmation Bias Simulations. Five years of original dataset (2012 - 2016), effective two-year rolling window model, showing every other simulated year for 'α' = 0.1 and 'β' = 0.5.

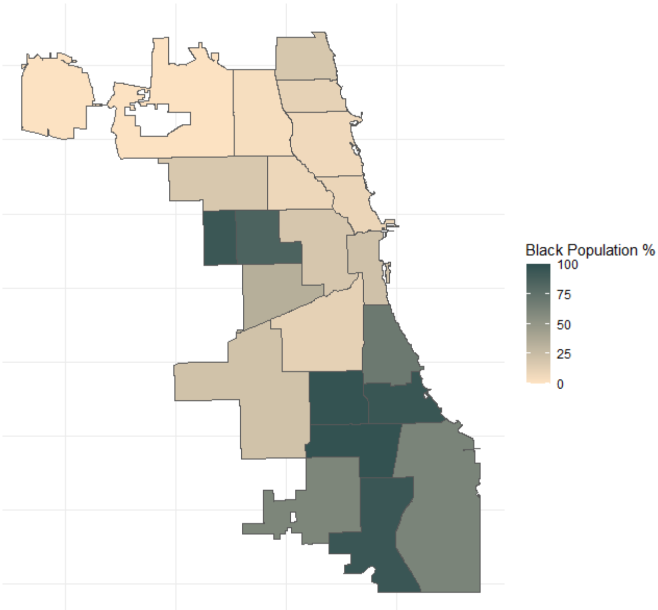
3.3 Visualization

3.3.1 District Locations and Black Population Percentages

Below are two maps of Chicago police districts, one with district numbers labelled (**Figure 20**), and the other with Black population percentage shown per district (**Figure 21**). These are provided for comparison with the visualizations shown further below in **Section 3.3.2** of the effects of worsening racial bias as a result of the feedback loop just simulated above.

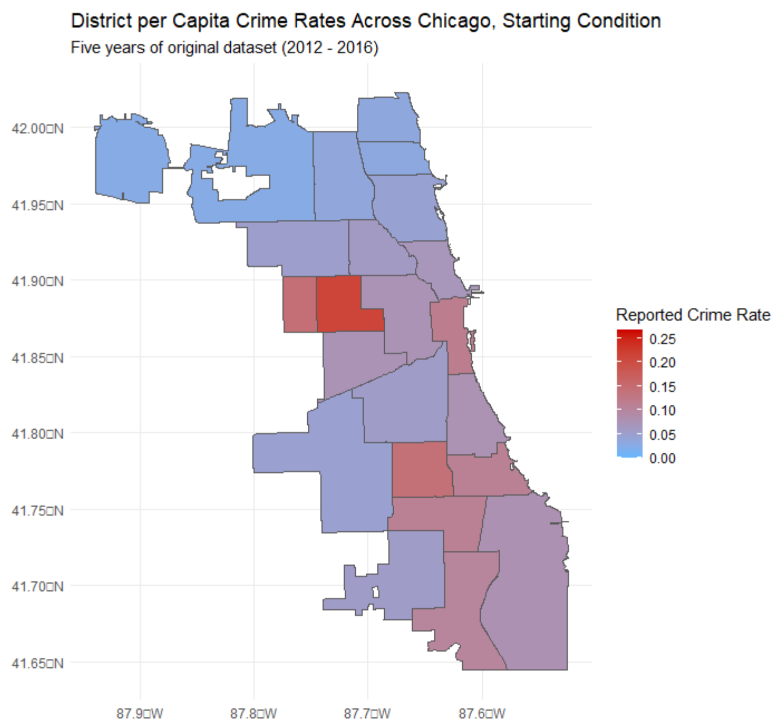
Figure 20 (left). Map of labelled Chicago police districts. **Figure 21 (right).** Map showing district Black percentage population per district.





3.3.2 Effect of Model Feedback on District Crime Rates

Shown below (**Figures 22a**, **22b**, and **22c**) are spatiotemporal visualizations of the effects on district crime rate rates of overcompensation plus confirmation bias for the "best-approximation" case simulation ($\alpha = 0.1$, $\beta = 0.5$, effective two-year rolling window). Visualizations are given for three distinct points during simulation: the starting point, the fourth simulated year ("Gen IV"), and the eighth simulated year ("Gen VIII"). These visualizations are also shown layed adjacent to one another for easier visual comparison in **Figures 23a**, **23b**, and **23c**.



Figures 22a, 22b, & 22c. District per Capita Crime Rates Across Chicago: X. Starting Condition; Y. Fourth Simulated Year; Z. Eight Simulated Year. Five years of original dataset (2012 - 2016), effective two-year rolling window, 'α' = 0.1, 'β' = 0.5.

Figure 22a. Initial Condition.

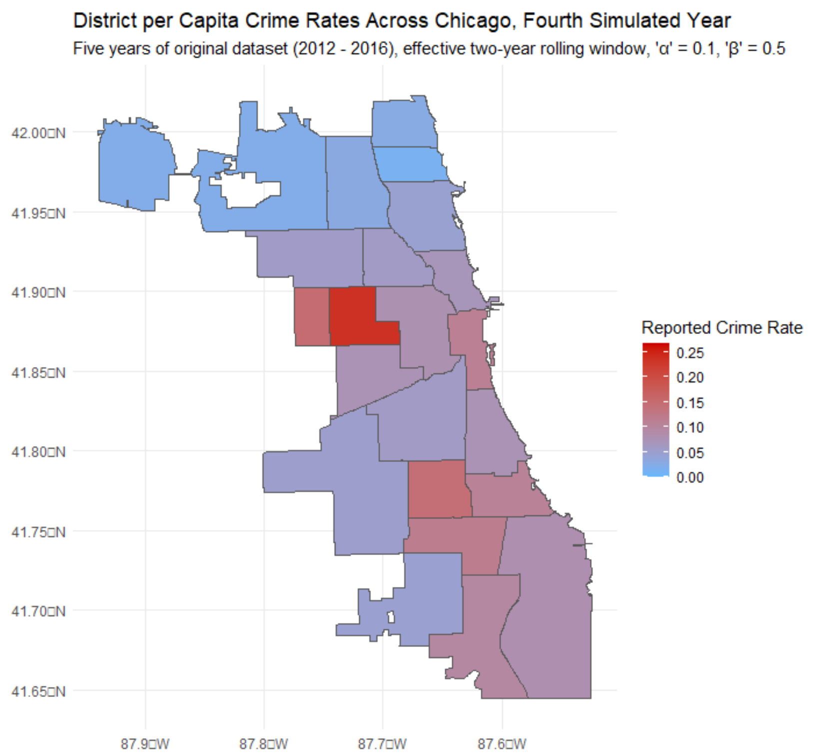


Figure 22b. Fourth Simulated Year.

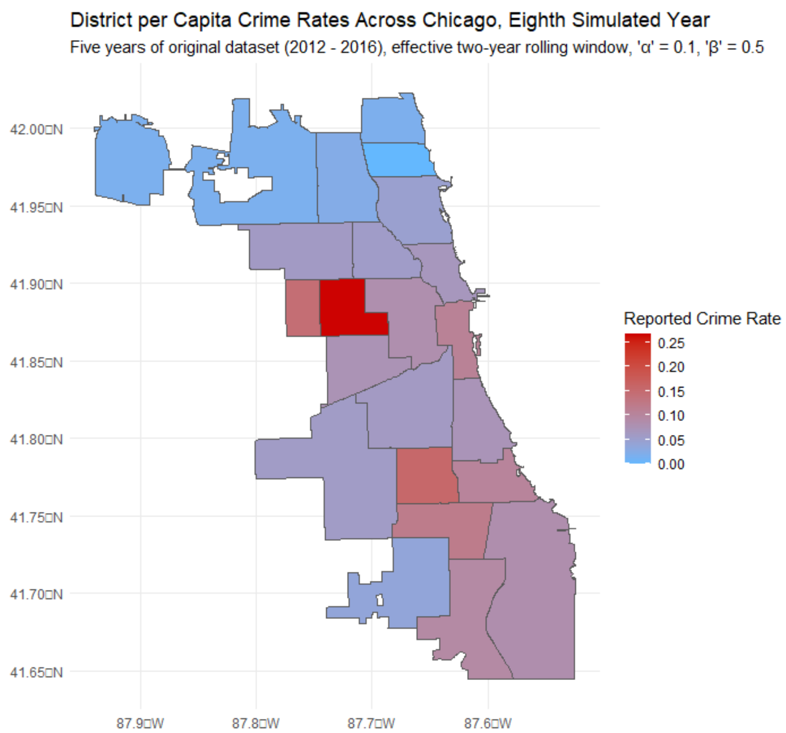
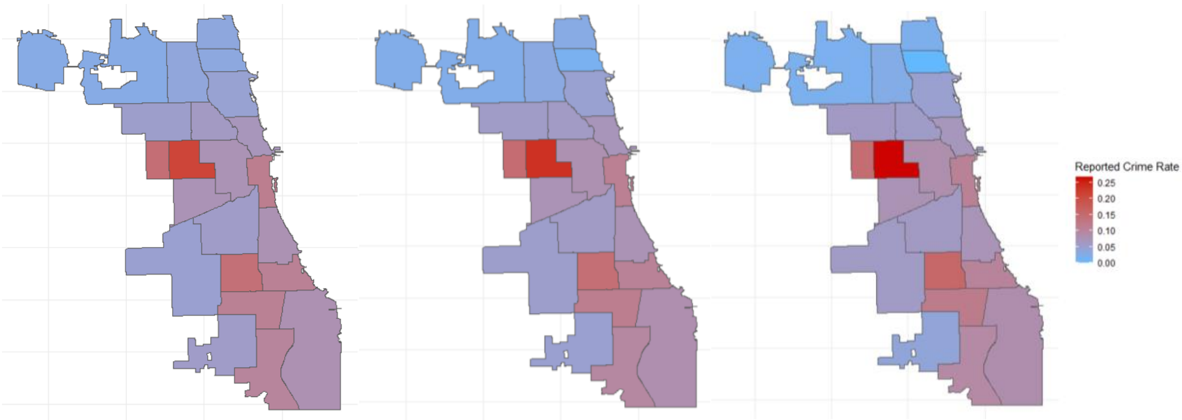


Figure 22c. Eighth Simulated Year.

Figures 23a, 23b, and 23c (left to right). District per Capita Crime Rates Across Chicago as shown above, layed adjacent to one another for easier visual comparison. **Figure 23a**: Starting Condition; **Figure 23b**: Fourth Simulated Year; **Figure 23c**: Eight Simulated Year.



3.4 Proof-of-concept Simulations

3.4.1 Overcompensation (Effective Two-year Rolling Window)

Shown below in **Figure 24** is the proof-of-concept simulation of the effect of overcompensation on district crime count over the course of eight years, where $\alpha = 0.1$. The substitution of real data with dummy data yielded similar results to the simulations with real data, thus proving the validity of the approach used here. From this result, we can surmise that the changes observed are those from the difference in crime report rates between districts.

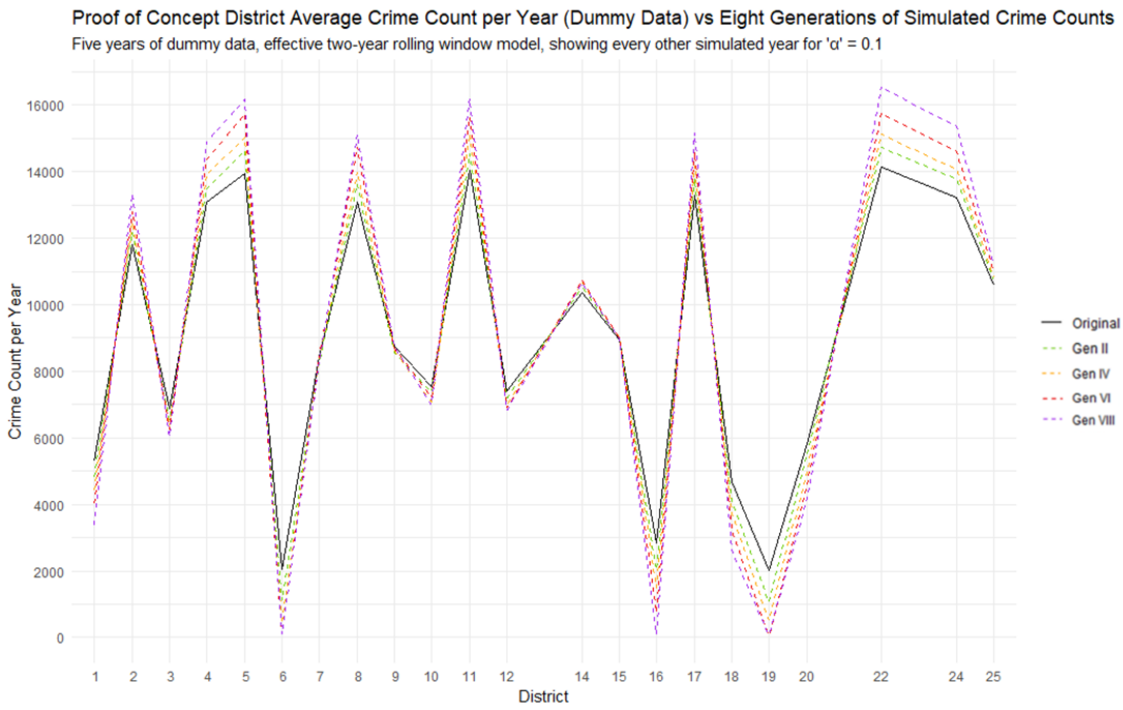


Figure 24. Proof of Concept Model using Dummy Dataset, with Confirmation Bias also included, showing every other simulated year for 'α' = 0.1 and 'β' = 0.5. Dummy dataset consisted of five years of crime counts randomly sampled from Poisson distributions for each district, where λ was randomly assigned for each district.

3.4.2 Overcompensation Plus Confirmation Bias (Effective Two-year Rolling Window)

Shown below in **Figure 25** is the proof-of-concept simulation of the effect of overcompensation plus confirmation bias on district crime count over the course of eight years, where $\alpha = 0.1$ and $\beta = 0.5$. The results and, thus, the inferences to be made are the same here as in **Section 3.4.1** above.

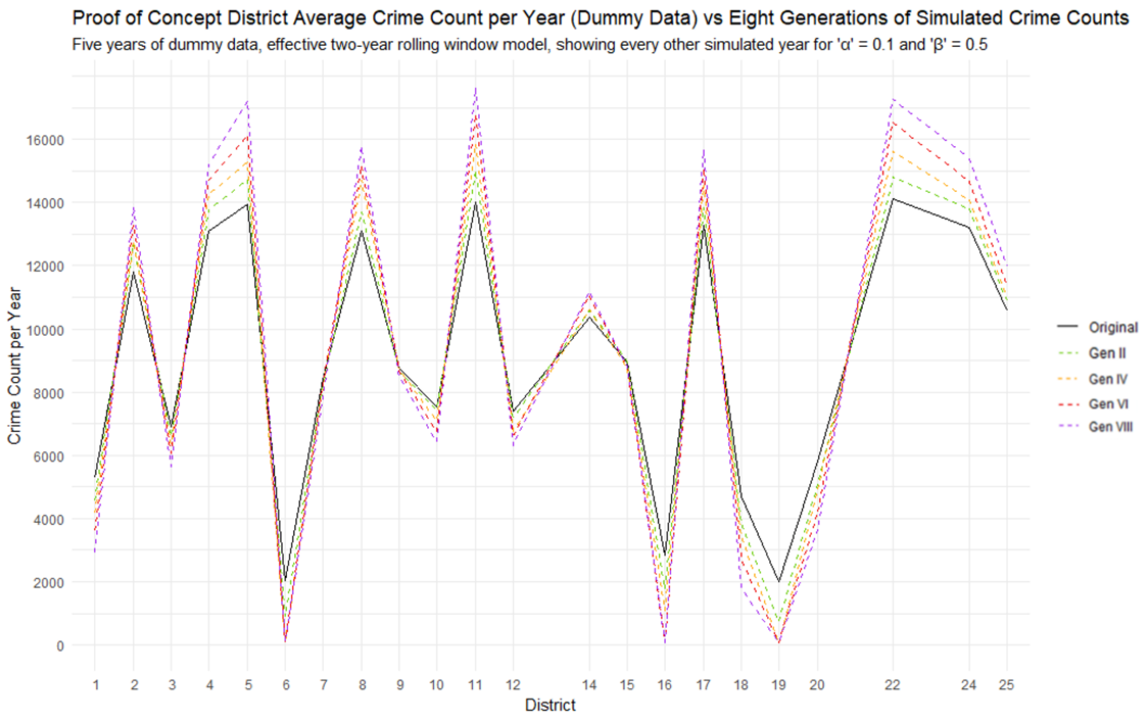


Figure 25. Proof of Concept Model using Dummy Dataset, with Confirmation Bias also included, showing every other simulated year for 'α' = 0.1 and 'β' = 0.5. Dummy dataset consisted of five years of crime counts randomly sampled from Poisson distributions for each district, where λ was randomly assigned for each district.

4 Discussion

4.1 Summary of Key Findings

In a study which constitutes a novel approach to modelling the evolution of racial bias within predictive policing algorithms, we see remarkable effects on crime rates representative of deepening racial bias, given a plausible degree of simulated behavioural bias, for both overcompensation and confirmation bias. In certain conditions, the effects observed were so significant that the system ended up following a runaway feedback loop. Meanwhile, in others, an initial change in crime rates, followed by plateau.

A key finding of this study is that of the comparative effects both of overcompensation and of confirmation bias on district crime rates. In what we describe here as the "best-approximation" case simulation ($\alpha = 0.1$, $\beta = 0.5$), overcompensation was observed to have an additive year-on-year effect on district crime counts, while confirmation bias exhibited a compounding effect. Both effects, while differing in their respective trajectories, are considerable.

As mentioned, in this best-approximation case, the effect of overcompensation is modulated by a factor of $\alpha = 0.1$, and confirmation bias by a factor of $\beta = 0.5$. To put these settings into context, one can consider the following hypothetical: say a given district is forecast to have 20 crimes occur in a given time period, where the district mean forecast is just 10. Given the parameter setting of $\alpha = 0.1$, this results in an effective forecast (to be used in the ensuing crime count simulation) of 21. Thus, because the given district forecast is over the district mean by so much, resourcing will be disproportionately assigned in a manner such that the outcome is equivalent to an additional 1 crime report in the given district, during the given time period. This effect goes both ways, and so this additional crime report will be cancelled out by 1 less crime report occurring elsewhere. Meanwhile, say the total crime count for the same district during the most recent full year is 11,000, compared to the previous year's total of 10,000. Given the parameter setting of $\beta = 0.5$, the simulated effect of confirmation bias on the initial forecast will increase it from 20 to an effective forecast of 21 (the effects of the two biases are independent of one another within each iteration). Ultimately, then, the combined effect of overcompensation and confirmation bias in this example – where $\alpha = 0.1$ and $\beta = 0.5$ – would lead to an increase in expected crime report count from 20 to 22.

Another key finding of this study is that the implementation of a rolling window during model training proved to be a major determinant of a system's capacity for the exacerbation of racial bias to occur year-on-year. Without the presence of a rolling window, a dilution effect was observed, wherein the new and more biased data is added to the equally weighted preceding years' data, and so their influence on the updated model is greatly limited. In contrast, with the institution of an effective two-year rolling window within simulations, changes in crime rates observed during a simulated year go on to have a considerably larger impact on the updated model, as recent years are weighted more heavily than older years. Thus, the newly trained model represents a more up-to-date one when using a rolling window, and so predictions are kept more relevant.

As explained above, there exists sufficient evidence (Feng *et al.*, 2019; Ouimet, 2004: Butts & Evans, 2014) to reasonably suggest that predictive policing models currently used by police forces might use a rolling window, in preference of having no rolling window. Further, it is apparent that utilizing even a relatively small rolling window does not significantly hinder model performance, as found here as well as in the literature (Feng *et al.*, 2019), providing all the more reason why police forces might use rolling windows in their predictive models.

The two general simulation trajectories are both meaningful results, with serious implications regarding future consequences of using predictive policing tools in the real world. However, it must be noted that these striking results rely mainly on the overarching assumptions that police resourcing is allotted year-on-year according broadly to the forecast output by the predictive model – without police detecting and accounting for any deepening model racial bias –, and also that any increased (or decreased) resourcing leads to a proportional increase (or decrease) in crime reports in a given district. In reality, this may not necessarily be the case, particularly with reference to the former assumption, as police departments may cotton on to the effects of such feedback loops – particularly in the case of runaway effects and in later years –, and may, as a result, adjust resourcing accordingly. Nonetheless, projections like these are still necessary as it is far more important to identify and address the effects of increasing racial bias before they manifest.

This is why, at the same time, if it is the case that crime rates initially increase (and equally decrease) before going on to plateau, this is still an important result; police departments will be less likely to take notice of this change if it does not continue to change further. Therefore, it is possible that racial bias could increase as a result of the effects proposed here, and sit at this new level, going unnoticed.

In order to carry out simulations, a predictive model was created to emulate such models used by police forces today, such as Geolitica in the US. Negative Binomial regression proved better than Poisson regression in modelling the crime report data, likely due to the fact that the former takes into account the overdispersion present in the count data.

One should note that the response variable used in model training was “crime reports”, and not “arrests”. This choice represents an assumption made about – and sympathetic to – current predictive policing models; the reasoning behind this choice is outlined earlier in **Section 2.1**. However, if police departments were to use arrests as the response variable – which is suggested to be even more racially biased than crime report data (Heaven, 2021; Headley & Wright, 2020) –, any initial racial bias in the model would likely be more significant, and so, too, would be the extent any ensuing feedback loop.

Also noteworthy is the fact that such algorithms, for example Geolitica, update every day (*geolitica.com*, 2023), and not just every year, as modelled here. In this case, the effects found here would be expected to be more significant, given this practice. Additionally, they would likely manifest more gradually, and therefore would perhaps be more likely to go unnoticed by police departments for longer (akin to a frog in boiling water).

Added validity to the findings of this study comes from two proof-of-concept experiments carried out. Firstly, behavioural bias effects were set to zero during simulation, resulting in simulated district crime counts matching those of the original data, and hence proving that the approaches utilized for model construction and crime count simulation are valid. Secondly, dummy data was used for initial model construction – introducing behavioural bias terms resulted in similar effects as those seen using real data, thus proving that the signal observed is solely that generated by differential district crime rates.

Ultimately, then, the simulations carried out in this study returned significant evidence to support the main hypothesis proposed here. That is, that by factoring in the behavioural biases of overcompensation and confirmation bias, already racially biased predictive policing models have the capacity to become even more-so, through the emergence of coevolutionary feedback loops between machine and human.

4.2 Limitations and Further Study

The final model used for simulations, while somewhat useful at predicting crime counts, is not a perfect model. This is due mainly to the fact that crime occurrence is inherently very difficult to predict; there are myriad contributing factors, most of which are almost impossible to quantify, and, therefore, a considerable amount of what determines crime occurrence may be simply considered chance. This is the same problem presumably encountered by users of such predictive models in the real world. The somewhat-limited accuracy of our predictive model is also due to the fact that several trade-offs had to be made, mainly in order to minimize computational complexity. Additionally, as alluded to just above, the effect of year contributes a notable effect on crime report count; this is not accounted for in our model, due to the nature of the intended use of the predictive model. However, it is still clear that a reasonable amount of variation in crime report count is being accounted for. More importantly – as observed in the analysis above –, a major proportion of the signal detected comes from the "`district`" predictor.

If it were desired to more accurately emulate the predictive tools used in the real world, one might consider using data taken at an hourly level (as opposed to a half-day level) to achieve greater resolution. In addition, a slight increase in predictive power might be found in the use of zero-inflated model types such as ZINB or ZIP models, as these account for excess zeroes which might be present to a certain extent in the data. Further, one could also go on to engineer an additional feature for "special events" in order to add extra detail to the model. As already described above, this would describe whether or not there is a certain event, such as a public holiday or a sporting event, occurring on the given day – even perhaps around a given time range during that day.

As already detailed, the key results discussed here are mainly those from our best-approximation of the behavioural biases simulated. In order to empirically quantify the actual extent of the two behavioural biases investigated here, results could be taken from experiments run in which participants are asked to judge how to distribute police resources according to various different crime count forecasts.

In addition to the two covered here, other behavioural biases might be investigated in this context, such as "conformity bias". Here, it could be that perceptions and their resulting behaviours, having been already altered by deepening racial bias within the predictive model, are disproportionately adopted if they come to represent the majority case. Also, other approaches might be utilized to model such a system, such as agent-based methods (Cavalli-Sforza & Feldman, 1981; Bonabeau, 2002).

Note that the assumption is being made here that each behavioural bias is linear in how it determines effective forecasts (and ultimately, simulated crime counts). To model the behavioural biases exponentially, one might use z-scores (as previously mentioned). If doing so, it would have to be made sure that total crime count remains the same; this could be done by randomly sampling across all timepoints and districts until the total crime count is lowered (or raised) back to the previous year's total count. Alternatively, one could add an exponential term to the forecast biasing formula (maintaining total crime count in the same manner).

In order to obtain the most realistic picture possible of the true trajectories of the proposed systems, we would need to better inspect the two main assumptions which have been made in this study. Namely, a) that police roughly follow forecasts year-on-year without detecting and adjusting for any exacerbation of racial bias in the model, and b) that an increase in police resourcing results in the same increase in crime reports, independent of current district police resourcing. The former is arguably the most crucial, and will likely break down at some stage over time, as police will inevitably use common-sense, as well as citizen crime reporting behaviour to keep their perceived distribution of crime rates grounded in reality. However, this assumption is difficult to properly investigate. The latter, on the other hand, may be feasibly tested by looking at data regarding police distributions, and lining these to crime report rates.

4.3 Implications for Policy & Practice

It has already been suggested in recent years that predictive policing tools lead to biased outcomes that do not improve public safety (Heaven, 2021). The findings of this study make for striking proof of this.

Here, we have provided evidence for a deepening of racial bias in the algorithm. In certain conditions this effect stabilises, and in some it is a runaway effect. In a real-world context, the latter would inevitably get to the point where police departments would realise this effect, and either have to compensate for it, or scrap the use of the predictive tool entirely. Until this happens, however, these algorithms offer a great capacity for harm to be done.

It has been suggested that using predictive policing tools may be entirely counterproductive with regard to the central aim of law enforcement – to minimize crime. If differential enforcement emboldens the overlooked group more than it deters the scrutinized group, it may only make the problem worse (Harcourt, 2005). So, as a net result of the effects proposed here, not only might minority groups become even more oppressed by law enforcement, but those who don't suffer as much from this process might, in fact, be more inclined than before to committing crimes.

On another note, it is possible that any increase in crime report rates (or arrest rates) in Blacks that come as a result of the system proposed here might then feed into other racially biased systems downstream within the criminal justice system. Take recidivism risk estimators such as COMPAS for example. If, as a result of the mechanisms investigated here, Blacks on average are reported and/or arrested even more than non-Blacks, then this could factor into the criteria used in determining recidivism rates, ultimately resulting in even higher reported risks for Blacks versus non-Blacks.

Having investigated the effects of human behavioural bias, this study might inform not just on the implementation of predictive AI tools such as those utilised in predictive policing, but also on the interpretations of these models. For instance, given the results of the study, it might be advisable to take police officers in contact with predictive policing technologies and educate them on the dangers of over-compensation and of confirmation bias in relation to racial bias, and their potential consequences when using these tools in the real-world.

Otherwise, we can try to ameliorate any racial bias present in predictive models, in a process known as debiasing. Although counterintuitive, it may in fact be more harmful in certain systems to omit protected attributes such as gender, disability status, or – in this case –, race. This is because the effects of these factors can be redundantly encoded in the other studied variables, and so are still implicitly included in the predictive model. Omitting such attributes in these cases can, therefore, make it difficult to impossible to properly debias a given model. Mitigation of racial bias might be possible by taking into account the Black population percentage of each area and using this to correct the crime forecast. For this, more information would be needed in order to break down the effects of Black population percentage on crime reports into those which lead to an increase only in crime report occurrence, versus those which lead to an increase in actual crime occurrence, and to then control solely for the former effect. Analysis might be done to formally quantify how much Black population percentage can contribute to poverty rates, and then to what degree poverty rates influence crime rates. Alternatively, one might look at crime types which would tend to have more uniform reporting rates, such as homicide or other violent crimes, in order to get a truer, less biased picture of crime rates between areas – something closer to a ground-truth (Corbett-Davies *et al.*, 2017). Alternatively, still, some developers of predictive policing tools say that they have started using victim reports to get a more accurate picture of crime rates in different neighbourhoods. In theory, victim reports should be less biased because they aren't affected by police prejudice or feedback loops. However, this doesn't have much of an effect on controlling bias, as victim reports, too, have been shown to be racially biased (Heaven, 2021; Akpinar *et al.*, 2021). Further yet, it might be possible to somewhat debias predictive policing algorithms like Geolitica by ascertaining the ratio of reported crimes to unreported crimes across different areas. This seems, by definition, a difficult task. However, such work has been done within the context of drug-related crimes (Lum & Iassac, 2016), where data from the National Survey on Drug Use and Health was used to estimate illegal drug use. This estimation was then compared to the record of arrests in the same city to try to elucidate a truer representation of crime incidence. It is the use of corrected, debiased metrics like these toward which we should move, in the first steps to dealing with algorithm biases, not just within the realm of predictive policing, but within any domain where algorithms make decisions that impact people's lives.

Predictive policing models and their applications are currently mostly shrouded in mystery. Until we know how the algorithms work and what data they use, and how police forces utilize their outputs, modelling the evolution of racial bias in these systems will always remain something of a best guess. Although Geolitica states that it utilizes only “crime type, crime location and crime date/time” as predictors (*geolitica.com*, 2023), there is no further detail available to the public regarding how exactly they use them. Nor is it known to the public which jurisdictions use the tool, or how it is implemented in each jurisdiction. Information on other predictive policing tools is even more sparse. As with AI decision-making tools in general, there have been growing calls for transparency in predictive policing tools. As Rashida Richardson states: “The use of predictive policing must be treated with high levels of caution and mechanisms for the public to know, assess, and reject such systems are imperative” (Richardson *et al.*, 2019).

In the meantime, while we don’t know how the models are operating, or how to fix them, the answer – at least for now – might be a moratorium on predictive policing tools. There is currently considerable public pressure to dismantle these racially biased tools and the policies behind them. Early adopters of predictive policing tools, like Santa Cruz, have announced they will no longer use them. Moreover, there have been scathing official reports on the use of predictive policing by both the LAPD and the CPD (Heaven, 2021).

In any case, particularly given the findings of this study, it is clear that in order to minimise the harm caused by racial bias in predictive policing algorithms, it is of utmost importance that action be taken now, rather than later.

“The easiest moment in which to intervene is, of course, as soon as possible.”

– Brian Christian, The Alignment Problem (2021)

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Appendices

Appendix 1A: Full Column Descriptions of Original dataset:

Full column descriptions of Chicago crime dataset (source: https://data.cityofchicago.org/Public-Safety/clear/6bgw-6s23/data).

`ID` - Unique identifier for the record.

`Case Number` - The Chicago Police Department RD Number (Records Division Number), which is unique to the incident.

`Date` - Date when the incident occurred. This is sometimes a best estimate.

`Block` - The partially redacted address where the incident occurred, placing it on the same block as the actual address.

`IUCR` - The Illinois Uniform Crime Reporting code. This is directly linked to the Primary Type and Description. See the list of IUCR codes at https://data.cityofchicago.org/d/c7ck-438e.

`Primary Type` - The primary description of the IUCR code.

`Description` - The secondary description of the IUCR code, a subcategory of the primary description.

`Location Description` - Description of the location where the incident occurred.

`Arrest` - Indicates whether an arrest was made.

`Domestic` - Indicates whether the incident was domestic-related as defined by the Illinois Domestic Violence Act.

`Beat` - Indicates the beat where the incident occurred. A beat is the smallest police geographic area – each beat has a dedicated police beat car. Three to five beats make up a police sector, and three sectors make up a police district. The Chicago Police Department has 22 police districts. See the beats at https://data.cityofchicago.org/d/aerh-rz74.

`District` - Indicates the police district where the incident occurred. See the districts at https://data.cityofchicago.org/d/fthy-xz3r.

`Ward` - The ward (City Council district) where the incident occurred. See the wards at https://data.cityofchicago.org/d/sp34-6z76.

`Community Area` - Indicates the community area where the incident occurred. Chicago has 77 community areas. See the community areas at https://data.cityofchicago.org/d/cauq-8yn6.

`FBI Code` - Indicates the crime classification as outlined in the FBI's National Incident-Based Reporting System (NIBRS). See the Chicago Police Department listing of these classifications at http://gis.chicagopolice.org/clearmap_crime_sums/crime_types.html.

`X Coordinate` - The x coordinate of the location where the incident occurred in State Plane Illinois East NAD 1983 projection. This location is shifted from the actual location for partial redaction but falls on the same block.

`Y Coordinate` - The y coordinate of the location where the incident occurred in State Plane Illinois East NAD 1983 projection. This location is shifted from the actual location for partial redaction but falls on the same block.

`Year` - Year the incident occurred.

`Updated On` - Date and time the record was last updated.

`Latitude` - The latitude of the location where the incident occurred. This location is shifted from the actual location for partial redaction but falls on the same block.

`Longitude` - The longitude of the location where the incident occurred. This location is shifted from the actual location for partial redaction but falls on the same block.

`Location` - The location where the incident occurred in a format that allows for creation of maps and other geographic operations on this data portal. This location is shifted from the actual location for partial redaction but falls on the same block.

Appendix 1B: Full Column Descriptions of Engineered Features:

Full column descriptions of predictors engineered from the "`Date`" variable:

`date` – Month and day of month in "MM-DD" format.

`year` – Year in "YYYY" format.

`month` – Values from "01" to "12", where "01" represents January, and "12" represents December.

`day_of_week` – Values from "1" to "7", where "1" represents Monday, and "7" represents Sunday.

`hour_of_day` – Values of either "1" or "2" to represent "half-days", where "1" represents 01:00:00 – 11:59:59, and "2" represents 12:00:00 – 00:59:59. This variable initially took the form of values from "0" to "23", where "0" represented 00:00:00 – 00:59:59, and "23" represented 23:00:00 – 23:59:59. However, it was later decided to pivot to a variable which represented half-days at a time; the variable name was retained for ease of use.

Appendix 2: Removed Crime Types

Removed crime types unlikely to be detected during patrol – looking at "`Location Description`" column, the following values were excluded:

“RESIDENCE”, “APARTMENT”, “RESTAURANT”, “DEPARTMENT STORE”, “COMMERCIAL / BUSINESS OFFICE”, “CHA APARTMENT”, “BANK”, “HOTEL/MOTEL”, “CHA HALLWAY/STAIRWAY/ELEVATOR”, “CTA TRAIN”, “CTA BUS”, “HOSPITAL BUILDING/GROUNDS”, “AIRPORT/AIRCRAFT”, “CHURCH/SYNAGOGUE/PLACE OF WORSHIP”, “GOVERNMENT BUILDING/PROPERTY”, “SCHOOL, PRIVATE, BUILDING”, “NURSING HOME/RETIREMENT HOME”, “WAREHOUSE”, “MEDICAL/DENTAL OFFICE”, “FACTORY/MANUFACTURING BUILDING”, “LIBRARY”, “COLLEGE/UNIVERSITY GROUNDS”, “AIRPORT TERMINAL UPPER LEVEL - SECURE AREA”, “OTHER COMMERCIAL TRANSPORTATION”, “DAY CARE CENTER”, “MOVIE HOUSE/THEATER”, “COLLEGE/UNIVERSITY RESIDENCE HALL”, “AIRPORT TERMINAL LOWER LEVEL - NON-SECURE AREA”, “JAIL / LOCK-UP FACILITY”, “FEDERAL BUILDING”, “AIRPORT VENDING ESTABLISHMENT”, “ANIMAL HOSPITAL”, “BOAT/WATERCRAFT”, “AIRPORT BUILDING NON-TERMINAL - NON-SECURE AREA”, “AIRCRAFT”, “AIRPORT TERMINAL UPPER LEVEL - NON-SECURE AREA”, “AIRPORT TERMINAL LOWER LEVEL - SECURE AREA”, “CREDIT UNION”, “HOUSE”, “AIRPORT BUILDING NON-TERMINAL - SECURE AREA”, “SAVINGS AND LOAN”, “AIRPORT EXTERIOR - SECURE AREA”, “HALLWAY”, “AIRPORT TRANSPORTATION SYSTEM (ATS)”, “AIRPORT TERMINAL MEZZANINE - NON-SECURE AREA”, “CHA HALLWAY”, “BASEMENT”, “HOTEL”, “STAIRWELL”, “CLUB”, “OFFICE”, “RAILROAD PROPERTY”, “SCHOOL YARD”, “CHA STAIRWELL”, “CHA LOBBY”, “HOSPITAL”, “MOTEL”, “WOODED AREA”, “NURSING HOME”, “RIVER”, “CHA BREEZEWAY”, “CHA PLAY LOT”, “COACH HOUSE”, “CTA "L" PLATFORM”, “LAKE”, “SEWER”, “TRAILER”, “CHA ELEVATOR”, “CHURCH”, “COUNTY JAIL”, “CTA "L" TRAIN”, “CTA PROPERTY”, “FACTORY”, “LAUNDRY ROOM”, “LIVERY STAND OFFICE”, “PRAIRIE”, “PUBLIC HIGH SCHOOL”, “RIVER BANK”, “YMCA”, “BANQUET HALL”, “CLEANERS/LAUNDROMAT”, “ELEVATOR”, “FUNERAL PARLOR”, “GOVERNMENT BUILDING”, “JUNK YARD/GARBAGE DUMP”, “LAGOON”, “LIVERY AUTO”, “POOLROOM”, “PUBLIC GRAMMAR SCHOOL”, “ROOMING HOUSE”, “TRUCKING TERMINAL”

Appendix 3: Residual Analysis

Normal Q-Q Plot showing non-normality of dataset and Deviance-Residual plot showing non-homogeneity of variance.

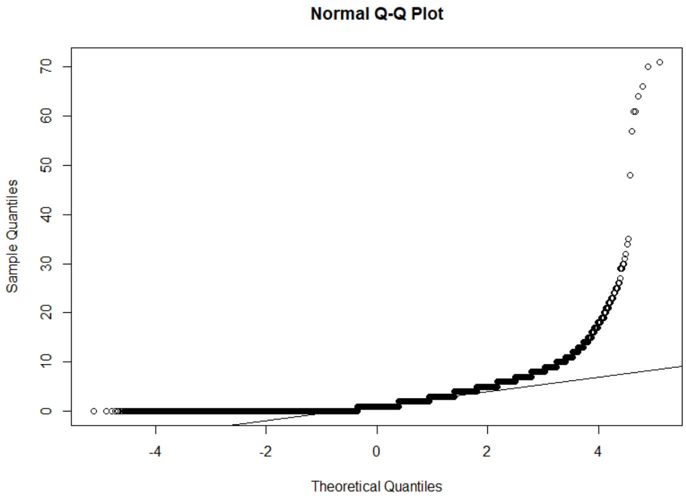

Figure A1. Normal Q-Q Plot of Crime Count data (half-day resolution) against uniform distribution line.

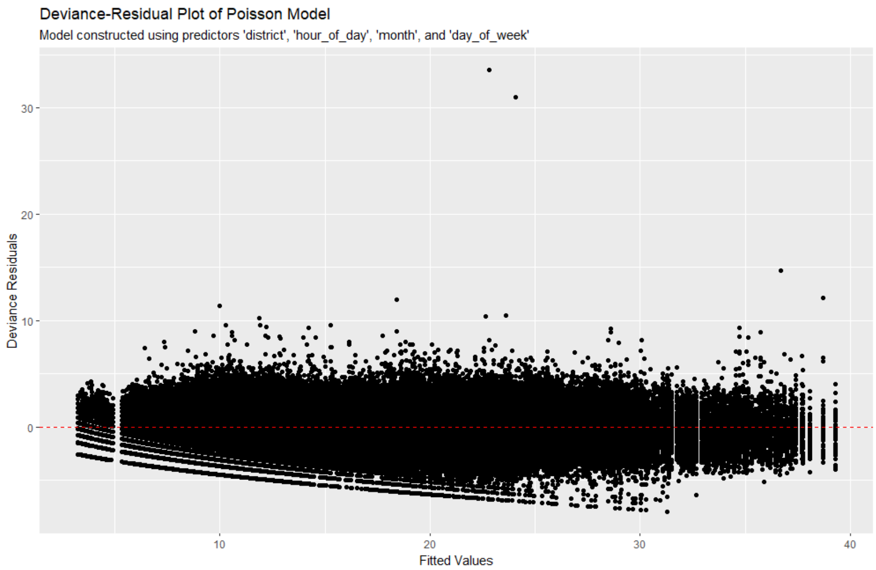

Figure A2. Deviance-Residual plot of Poisson regression Model. Model constructed using predictors "`district`", "`hour_of_day`", "`month`", and "`day_of_week`". The residuals are more spread out at the higher values of the fitted values. This indicates that the assumption of homogeneity of variance has been violated.

Appendix 4: Derivation of Predictor Variable Test Statistics

Output of "`summary()`" function for Negative Binomial regression model with all possible predictor variables included to elucidate predictor variable test statistics.

```
Call:
```

```
glm.nb(formula = count ~ hour + district + month + weekday +
date + year, data = chic, init.theta = 23.24075481, link = log)

Deviance Residuals:
Min       1Q   Median       3Q      Max
-6.4065  -0.7102  -0.0670   0.5714  16.0124

Coefficients: (11 not defined because of singularities)
Estimate Std. Error  z value Pr(>|z|)
(Intercept)  2.1690486  0.0137661  157.565  < 2e-16 ***
hour2        0.6576092  0.0013549  485.374  < 2e-16 ***
district2    0.3192931  0.0045146   70.725  < 2e-16 ***
district3    0.2838748  0.0045357   62.587  < 2e-16 ***
district4    0.4090465  0.0044638   91.637  < 2e-16 ***
district5    0.1612986  0.0046138   34.960  < 2e-16 ***
district6    0.4234777  0.0044560   95.036  < 2e-16 ***
district7    0.4855566  0.0044234  109.769  < 2e-16 ***
district8    0.6448625  0.0043474  148.332  < 2e-16 ***
district9    0.3852590  0.0044769   86.055  < 2e-16 ***
district10   0.2558098  0.0045529   56.186  < 2e-16 ***
district11   0.7302382  0.0043108  169.398  < 2e-16 ***
district12   0.4441407  0.0044449   99.920  < 2e-16 ***
district14   0.1918744  0.0045936   41.770  < 2e-16 ***
district15   0.2992584  0.0045264   66.113  < 2e-16 ***
district16  -0.2055008  0.0049005  -41.934  < 2e-16 ***
district17  -0.1748863  0.0048732  -35.887  < 2e-16 ***
district18   0.2400689  0.0045627   52.616  < 2e-16 ***
district19   0.3103200  0.0045199   68.657  < 2e-16 ***
district20  -0.7106478  0.0054596 -130.164  < 2e-16 ***
district22  -0.1019421  0.0048108  -21.190  < 2e-16 ***
district24  -0.1986255  0.0048943  -40.583  < 2e-16 ***
district25   0.5262099  0.0044030  119.511  < 2e-16 ***
month2       0.0741439  0.0297629    2.491 0.012733 *
month3       0.0752194  0.0184080    4.086 4.38e-05 ***
month4       0.1069447  0.0183036    5.843 5.13e-09 ***
month5       0.1946608  0.0180797   10.767  < 2e-16 ***
month6       0.2631128  0.0179245   14.679  < 2e-16 ***
month7       0.2869961  0.0178584   16.071  < 2e-16 ***
month8       0.2591246  0.0179198   14.460  < 2e-16 ***
month9       0.1979078  0.0180711   10.952  < 2e-16 ***
month10      0.3147798  0.0177890   17.695  < 2e-16 ***
month11      0.0733240  0.0183964    3.986 6.73e-05 ***
month12     -0.1623229  0.0191130   -8.493  < 2e-16 ***
weekday2     0.0307712  0.0025191   12.215  < 2e-16 ***
weekday3     0.0400685  0.0024986   16.036  < 2e-16 ***
weekday4     0.0283184  0.0025128   11.270  < 2e-16 ***
weekday5     0.0824298  0.0024937   33.055  < 2e-16 ***
weekday6     0.0292062  0.0025030   11.668  < 2e-16 ***
weekday7    -0.0209854  0.0025386   -8.267  < 2e-16 ***
date01-02   -0.0685244  0.0185866   -3.687 0.000227 ***
date01-03   -0.0053821  0.0184045   -0.292 0.769955
date01-04   -0.0275013  0.0184660   -1.489 0.136410
```

```
date01-05   -0.0141748  0.0184346   -0.769 0.441937
date01-06   -0.0361806  0.0184958   -1.956 0.050448 .
date01-07   -0.0018867  0.0184003   -0.103 0.918329
date01-08    0.0286402  0.0183169    1.564 0.117913
date01-09    0.0601219  0.0182173    3.300 0.000966 ***
date01-10    0.0510030  0.0182460    2.795 0.005185 **
date01-11    0.0702356  0.0181913    3.861 0.000113 ***
date01-12    0.0799327  0.0181720    4.399 1.09e-05 ***
date01-13    0.0806651  0.0181668    4.440 8.99e-06 ***
date01-14    0.0467061  0.0182634    2.557 0.010547 *
date01-15    0.0872247  0.0181563    4.804 1.55e-06 ***
date01-16    0.0627756  0.0182100    3.447 0.000566 ***
date01-17    0.0526757  0.0182414    2.888 0.003881 **
date01-18    0.0271843  0.0183096    1.485 0.137625
date01-19    0.0362567  0.0185067    1.959 0.050100 .
date01-20    0.0303629  0.0185280    1.639 0.101263
date01-21   -0.0324089  0.0187094   -1.732 0.083232 .
date01-22   -0.0163045  0.0186573   -0.874 0.382176
date01-23    0.0302699  0.0185101    1.635 0.101982
date01-24    0.0456912  0.0184754    2.473 0.013396 *
date01-25    0.0516370  0.0184570    2.798 0.005147 **
date01-26    0.0416366  0.0184914    2.252 0.024343 *
date01-27    0.0135294  0.0185767    0.728 0.466430
date01-28    0.0265481  0.0185354    1.432 0.152061
date01-29    0.0217360  0.0185457    1.172 0.241186
date01-30    0.0158458  0.0185516    0.854 0.393025
date01-31   -0.0287419  0.0186925   -1.538 0.124142
date02-01   -0.0690398  0.0298656   -2.312 0.020795 *
date02-02   -0.1495486  0.0300231   -4.981 6.32e-07 ***
date02-03   -0.1486319  0.0300253   -4.950 7.41e-07 ***
date02-04   -0.1275884  0.0299796   -4.256 2.08e-05 ***
date02-05   -0.1026192  0.0299340   -3.428 0.000608 ***
date02-06   -0.0837286  0.0298871   -2.801 0.005087 **
date02-07   -0.0695191  0.0298711   -2.327 0.019949 *
date02-08   -0.0806739  0.0298868   -2.699 0.006948 **
date02-09   -0.0826390  0.0298959   -2.764 0.005706 **
date02-10   -0.1090423  0.0299489   -3.641 0.000272 ***
date02-11   -0.1029928  0.0299328   -3.441 0.000580 ***
date02-12   -0.1297691  0.0299857   -4.328 1.51e-05 ***
date02-13   -0.0920228  0.0299025   -3.077 0.002088 **
date02-14   -0.0890900  0.0299070   -2.979 0.002893 **
date02-15   -0.0766891  0.0298795   -2.567 0.010270 *
date02-16   -0.0773411  0.0298862   -2.588 0.009657 **
date02-17   -0.0915453  0.0299161   -3.060 0.002213 **
date02-18   -0.0566165  0.0298473   -1.897 0.057845 .
date02-19   -0.0646942  0.0298639   -2.166 0.030288 *
date02-20   -0.0492533  0.0298247   -1.651 0.098651 .
date02-21   -0.0449200  0.0298268   -1.506 0.132059
date02-22   -0.0633270  0.0298552   -2.121 0.033910 *
date02-23   -0.0236066  0.0297899   -0.792 0.428106
date02-24   -0.0451507  0.0298313   -1.514 0.130145
date02-25   -0.0405980  0.0298186   -1.361 0.173356
```

```
date02-26   -0.0979304  0.0299252   -3.273 0.001066 **
date02-27   -0.0732341  0.0298679   -2.452 0.014209 *
date02-28   -0.0636268  0.0298604   -2.131 0.033105 *
date02-29           NA         NA       NA       NA
date03-01   -0.0695132  0.0185796   -3.741 0.000183 ***
date03-02   -0.0575495  0.0185425   -3.104 0.001912 **
date03-03   -0.0575201  0.0185572   -3.100 0.001938 **
date03-04   -0.0628354  0.0185628   -3.385 0.000712 ***
date03-05   -0.0738421  0.0185864   -3.973 7.10e-05 ***
date03-06   -0.0137469  0.0184245   -0.746 0.455595
date03-07    0.0150513  0.0183349    0.821 0.411699
date03-08    0.0057352  0.0183660    0.312 0.754835
date03-09   -0.0317028  0.0184685   -1.717 0.086055 .
date03-10   -0.0163490  0.0184393   -0.887 0.375275
date03-11    0.0040046  0.0183732    0.218 0.827462
date03-12    0.0062137  0.0183589    0.338 0.735018
date03-13   -0.0043174  0.0183982   -0.235 0.814468
date03-14    0.0254842  0.0183066    1.392 0.163897
date03-15    0.0271140  0.0183076    1.481 0.138601
date03-16    0.0066332  0.0183616    0.361 0.717909
date03-17    0.0014203  0.0183897    0.077 0.938436
date03-18    0.0047504  0.0183712    0.259 0.795962
date03-19   -0.0178485  0.0184257   -0.969 0.332708
date03-20   -0.0322546  0.0184767   -1.746 0.080865 .
date03-21   -0.0467993  0.0185078   -2.529 0.011451 *
date03-22   -0.0276624  0.0184592   -1.499 0.133984
date03-23   -0.0230081  0.0184440   -1.247 0.212230
date03-24   -0.0173312  0.0184421   -0.940 0.347339
date03-25   -0.0278022  0.0184621   -1.506 0.132092
date03-26   -0.0030765  0.0183846   -0.167 0.867103
date03-27   -0.0212465  0.0184455   -1.152 0.249382
date03-28   -0.0115729  0.0184083   -0.629 0.529557
date03-29   -0.0091008  0.0184071   -0.494 0.621009
date03-30    0.0196881  0.0183259    1.074 0.282675
date03-31           NA         NA       NA       NA
date04-01    0.0100243  0.0181644    0.552 0.581040
date04-02   -0.0408259  0.0182945   -2.232 0.025642 *
date04-03   -0.0461459  0.0183223   -2.519 0.011784 *
date04-04   -0.0470700  0.0183120   -2.570 0.010157 *
date04-05   -0.0454289  0.0183160   -2.480 0.013128 *
date04-06   -0.0304866  0.0182695   -1.669 0.095174 .
date04-07   -0.0652419  0.0183844   -3.549 0.000387 ***
date04-08   -0.0489304  0.0183270   -2.670 0.007588 **
date04-09   -0.0215860  0.0182411   -1.183 0.236662
date04-10    0.0185748  0.0181446    1.024 0.305972
date04-11   -0.0249668  0.0182504   -1.368 0.171308
date04-12   -0.0137109  0.0182279   -0.752 0.451936
date04-13   -0.0366902  0.0182868   -2.006 0.044816 *
date04-14    0.0207113  0.0181461    1.141 0.253719
date04-15    0.0491726  0.0180607    2.723 0.006476 **
date04-16   -0.0126549  0.0182166   -0.695 0.487249
date04-17    0.0072192  0.0181751    0.397 0.691218
```

```
date04-18   -0.0041782  0.0181935   -0.230 0.818363    
date04-19   -0.0126114  0.0182249   -0.692 0.488946    
date04-20    0.0066808  0.0181679    0.368 0.713078    
date04-21   -0.0044091  0.0182140   -0.242 0.808724    
date04-22    0.0137188  0.0181545    0.756 0.449845    
date04-23   -0.0025615  0.0181890   -0.141 0.888007    
date04-24    0.0056859  0.0181793    0.313 0.754456    
date04-25   -0.0005833  0.0181838   -0.032 0.974412    
date04-26    0.0101400  0.0181632    0.558 0.576660    
date04-27   -0.0030788  0.0181943   -0.169 0.865625    
date04-28    0.0047130  0.0181892    0.259 0.795551    
date04-29    0.0337038  0.0181013    1.862 0.062609 .  
date04-30           NA         NA       NA       NA    
date05-01   -0.0202391  0.0177878   -1.138 0.255201    
date05-02   -0.0657893  0.0179016   -3.675 0.000238 ***
date05-03   -0.0543532  0.0178737   -3.041 0.002358 ** 
date05-04   -0.0440291  0.0178459   -2.467 0.013618 *  
date05-05   -0.0012411  0.0177482   -0.070 0.944253    
date05-06   -0.0427987  0.0178453   -2.398 0.016471 *  
date05-07   -0.0028382  0.0177361   -0.160 0.872862    
date05-08    0.0002311  0.0177349    0.013 0.989602    
date05-09   -0.0021788  0.0177348   -0.123 0.902221    
date05-10    0.0099393  0.0177063    0.561 0.574563    
date05-11   -0.0084045  0.0177530   -0.473 0.635918    
date05-12    0.0135872  0.0177104    0.767 0.442968    
date05-13    0.0148170  0.0176962    0.837 0.402426    
date05-14    0.0416422  0.0176243    2.363 0.018139 *  
date05-15    0.0385838  0.0176383    2.188 0.028706 *  
date05-16    0.0522458  0.0175987    2.969 0.002990 ** 
date05-17    0.0519363  0.0176016    2.951 0.003171 ** 
date05-18    0.0475023  0.0176126    2.697 0.006995 ** 
date05-19    0.0440833  0.0176339    2.500 0.012422 *  
date05-20    0.0497348  0.0176092    2.824 0.004737 ** 
date05-21    0.0374420  0.0176347    2.123 0.033736 *  
date05-22    0.0307220  0.0176578    1.740 0.081886 .  
date05-23    0.0553191  0.0175912    3.145 0.001663 ** 
date05-24    0.0597547  0.0175825    3.399 0.000677 ***
date05-25    0.0294052  0.0176574    1.665 0.095848 .  
date05-26    0.0069127  0.0177274    0.390 0.696579    
date05-27    0.0332919  0.0176498    1.886 0.059262 .  
date05-28    0.0566070  0.0175875    3.219 0.001288 ** 
date05-29    0.0587738  0.0175886    3.342 0.000833 ***
date05-30    0.0566384  0.0175880    3.220 0.001281 ** 
date05-31           NA         NA       NA       NA    
date06-01   -0.0559373  0.0175406   -3.189 0.001428 ** 
date06-02    0.0004866  0.0174112    0.028 0.977705    
date06-03   -0.0108122  0.0174310   -0.620 0.535069    
date06-04   -0.0232484  0.0174541   -1.332 0.182868    
date06-05   -0.0264197  0.0174714   -1.512 0.130491    
date06-06   -0.0203292  0.0174475   -1.165 0.243953    
date06-07   -0.0155592  0.0174406   -0.892 0.372325    
date06-08   -0.0124820  0.0174317   -0.716 0.473959    
```

```
date06-09   -0.0085966  0.0174335   -0.493 0.621938
date06-10    0.0033143  0.0173964    0.191 0.848906
date06-11    0.0100041  0.0173726    0.576 0.564712
date06-12    0.0082043  0.0173861    0.472 0.637007
date06-13   -0.0068136  0.0174142   -0.391 0.695602
date06-14    0.0198474  0.0173543    1.144 0.252767
date06-15   -0.0046206  0.0174124   -0.265 0.790729
date06-16    0.0061167  0.0173974    0.352 0.725147
date06-17    0.0056552  0.0173907    0.325 0.745041
date06-18   -0.0015686  0.0174007   -0.090 0.928171
date06-19   -0.0348107  0.0174924   -1.990 0.046586 *
date06-20    0.0029090  0.0173905    0.167 0.867153
date06-21   -0.0082358  0.0174225   -0.473 0.636420
date06-22   -0.0004582  0.0174023   -0.026 0.978993
date06-23   -0.0085544  0.0174334   -0.491 0.623646
date06-24   -0.0216186  0.0174577   -1.238 0.215589
date06-25   -0.0074274  0.0174150   -0.426 0.669749
date06-26    0.0087283  0.0173849    0.502 0.615621
date06-27    0.0027787  0.0173908    0.160 0.873055
date06-28    0.0144353  0.0173674    0.831 0.405876
date06-29    0.0269459  0.0173362    1.554 0.120111
date06-30           NA         NA       NA       NA
date07-01    0.0305098  0.0172042    1.773 0.076163 .
date07-02   -0.0347656  0.0173594   -2.003 0.045210 *
date07-03   -0.0638857  0.0174360   -3.664 0.000248 ***
date07-04   -0.0445259  0.0173827   -2.562 0.010422 *
date07-05    0.0242098  0.0172198    1.406 0.159746
date07-06   -0.0284718  0.0173440   -1.642 0.100675
date07-07    0.0073830  0.0172724    0.427 0.669054
date07-08   -0.0225810  0.0173314   -1.303 0.192611
date07-09   -0.0218597  0.0173277   -1.262 0.207112
date07-10    0.0044037  0.0172677    0.255 0.798704
date07-11   -0.0155505  0.0173116   -0.898 0.369042
date07-12    0.0187428  0.0172328    1.088 0.276760
date07-13    0.0197979  0.0172278    1.149 0.250481
date07-14    0.0089165  0.0172687    0.516 0.605620
date07-15    0.0427620  0.0171756    2.490 0.012785 *
date07-16    0.0120129  0.0172461    0.697 0.486080
date07-17    0.0034408  0.0172700    0.199 0.842076
date07-18    0.0031745  0.0172665    0.184 0.854128
date07-19   -0.0065225  0.0172931   -0.377 0.706047
date07-20    0.0189952  0.0172297    1.102 0.270260
date07-21    0.0161418  0.0172515    0.936 0.349441
date07-22    0.0203543  0.0172281    1.181 0.237419
date07-23   -0.0175067  0.0173171   -1.011 0.312041
date07-24   -0.0113809  0.0173057   -0.658 0.510770
date07-25    0.0132104  0.0172426    0.766 0.443586
date07-26    0.0197500  0.0172304    1.146 0.251699
date07-27    0.0241698  0.0172175    1.404 0.160382
date07-28    0.0235569  0.0172339    1.367 0.171657
date07-29    0.0147634  0.0172413    0.856 0.391844
date07-30    0.0083816  0.0172547    0.486 0.627138
```

```
date07-31           NA         NA      NA       NA    
date08-01    0.0638214  0.0172480   3.700 0.000215 ***
date08-02    0.0198304  0.0173610   1.142 0.253356    
date08-03    0.0143914  0.0173659   0.829 0.407263    
date08-04    0.0021367  0.0174154   0.123 0.902353    
date08-05    0.0254993  0.0173437   1.470 0.141499    
date08-06    0.0351143  0.0173176   2.028 0.042594 *  
date08-07    0.0080241  0.0173905   0.461 0.644509    
date08-08    0.0186770  0.0173547   1.076 0.281842    
date08-09    0.0116682  0.0173808   0.671 0.502010    
date08-10    0.0238423  0.0173431   1.375 0.169212    
date08-11    0.0449122  0.0173123   2.594 0.009480 ** 
date08-12    0.0162740  0.0173660   0.937 0.348695    
date08-13    0.0029461  0.0173951   0.169 0.865508    
date08-14    0.0129995  0.0173784   0.748 0.454447    
date08-15    0.0324997  0.0173216   1.876 0.060620 .  
date08-16    0.0046301  0.0173979   0.266 0.790140    
date08-17    0.0045841  0.0173897   0.264 0.792081    
date08-18   -0.0060608  0.0174356  -0.348 0.728131    
date08-19    0.0016380  0.0174016   0.094 0.925004    
date08-20    0.0254832  0.0173406   1.470 0.141677    
date08-21    0.0070147  0.0173930   0.403 0.686723    
date08-22   -0.0165306  0.0174407  -0.948 0.343223    
date08-23   -0.0066402  0.0174255  -0.381 0.703155    
date08-24    0.0206856  0.0173507   1.192 0.233181    
date08-25    0.0258192  0.0173579   1.487 0.136892    
date08-26    0.0240755  0.0173471   1.388 0.165177    
date08-27    0.0015957  0.0173984   0.092 0.926924    
date08-28   -0.0008002  0.0174121  -0.046 0.963345    
date08-29    0.0096217  0.0173766   0.554 0.579775    
date08-30    0.0112899  0.0173817   0.650 0.515997    
date08-31           NA         NA      NA       NA    
date09-01    0.1027384  0.0174782   5.878 4.15e-09 ***
date09-02    0.0510248  0.0175862   2.901 0.003715 ** 
date09-03    0.0325710  0.0176311   1.847 0.064694 .  
date09-04    0.0086303  0.0176964   0.488 0.625772    
date09-05    0.0369500  0.0176180   2.097 0.035968 *  
date09-06    0.0744490  0.0175330   4.246 2.17e-05 ***
date09-07    0.0823812  0.0175086   4.705 2.54e-06 ***
date09-08    0.0597034  0.0175814   3.396 0.000684 ***
date09-09    0.0441808  0.0176030   2.510 0.012079 *  
date09-10    0.0273189  0.0176441   1.548 0.121542    
date09-11    0.0454833  0.0176043   2.584 0.009776 ** 
date09-12    0.0369606  0.0176180   2.098 0.035915 *  
date09-13    0.0287022  0.0176449   1.627 0.103811    
date09-14    0.0435468  0.0176026   2.474 0.013365 *  
date09-15    0.0539316  0.0175955   3.065 0.002176 ** 
date09-16    0.0456433  0.0175994   2.593 0.009502 ** 
date09-17    0.0479133  0.0175932   2.723 0.006461 ** 
date09-18    0.0435559  0.0176090   2.473 0.013380 *  
date09-19    0.0546312  0.0175747   3.109 0.001880 ** 
date09-20    0.0739989  0.0175341   4.220 2.44e-05 ***
```

```
date09-21    0.0773330  0.0175207    4.414 1.02e-05 ***
date09-22    0.0671592  0.0175633    3.824 0.000131 ***
date09-23    0.0696881  0.0175408    3.973 7.10e-05 ***
date09-24    0.0693250  0.0175412    3.952 7.75e-05 ***
date09-25    0.0571708  0.0175756    3.253 0.001143 **
date09-26    0.0370859  0.0176177    2.105 0.035288 *
date09-27    0.0387322  0.0176200    2.198 0.027936 *
date09-28    0.0393579  0.0176129    2.235 0.025443 *
date09-29    0.0131983  0.0176970    0.746 0.455792
date09-30           NA         NA       NA       NA
date10-01   -0.0358683  0.0172172   -2.083 0.037225 *
date10-02   -0.1241736  0.0174504   -7.116 1.11e-12 ***
date10-03   -0.1158282  0.0174153   -6.651 2.91e-11 ***
date10-04   -0.1050236  0.0173983   -6.036 1.58e-09 ***
date10-05   -0.1063932  0.0173947   -6.116 9.57e-10 ***
date10-06   -0.0895310  0.0173694   -5.155 2.54e-07 ***
date10-07   -0.0923579  0.0173639   -5.319 1.04e-07 ***
date10-08   -0.0874190  0.0173449   -5.040 4.65e-07 ***
date10-09   -0.0784021  0.0173330   -4.523 6.09e-06 ***
date10-10   -0.1038130  0.0173843   -5.972 2.35e-09 ***
date10-11   -0.1074719  0.0174046   -6.175 6.62e-10 ***
date10-12   -0.1124945  0.0174104   -6.461 1.04e-10 ***
date10-13   -0.1520589  0.0175327   -8.673  < 2e-16 ***
date10-14   -0.1032719  0.0173918   -5.938 2.89e-09 ***
date10-15   -0.1009356  0.0173793   -5.808 6.33e-09 ***
date10-16   -0.1087501  0.0174104   -6.246 4.20e-10 ***
date10-17   -0.1006099  0.0173761   -5.790 7.03e-09 ***
date10-18   -0.1063996  0.0174018   -6.114 9.70e-10 ***
date10-19   -0.1031705  0.0173864   -5.934 2.96e-09 ***
date10-20   -0.0628693  0.0173022   -3.634 0.000279 ***
date10-21   -0.0667789  0.0172995   -3.860 0.000113 ***
date10-22   -0.1296685  0.0174537   -7.429 1.09e-13 ***
date10-23   -0.1239241  0.0174498   -7.102 1.23e-12 ***
date10-24   -0.1063952  0.0173910   -6.118 9.48e-10 ***
date10-25   -0.1138965  0.0174212   -6.538 6.24e-11 ***
date10-26   -0.1192163  0.0174278   -6.841 7.89e-12 ***
date10-27   -0.1232953  0.0174565   -7.063 1.63e-12 ***
date10-28   -0.1115212  0.0174131   -6.404 1.51e-10 ***
date10-29   -0.1018278  0.0173816   -5.858 4.67e-09 ***
date10-30   -0.0803906  0.0173381   -4.637 3.54e-06 ***
date10-31           NA         NA       NA       NA
date11-01    0.1961797  0.0178747   10.975  < 2e-16 ***
date11-02    0.0792249  0.0181561    4.364 1.28e-05 ***
date11-03    0.1055847  0.0181088    5.831 5.52e-09 ***
date11-04    0.0972384  0.0181148    5.368 7.97e-08 ***
date11-05    0.0982689  0.0181085    5.427 5.74e-08 ***
date11-06    0.0800099  0.0181639    4.405 1.06e-05 ***
date11-07    0.0774995  0.0181596    4.268 1.98e-05 ***
date11-08    0.0553224  0.0182272    3.035 0.002404 **
date11-09    0.0687392  0.0181834    3.780 0.000157 ***
date11-10    0.0904016  0.0181478    4.981 6.31e-07 ***
date11-11    0.0837420  0.0181496    4.614 3.95e-06 ***
```

```
date11-12    0.0484942  0.0182384    2.659 0.007840 **
date11-13    0.0492889  0.0182448    2.702 0.006902 **
date11-14    0.0449238  0.0182453    2.462 0.013808 *
date11-15    0.0860172  0.0181469    4.740 2.14e-06 ***
date11-16    0.0535162  0.0182235    2.937 0.003318 **
date11-17    0.0335985  0.0182981    1.836 0.066333 .
date11-18    0.0514566  0.0182344    2.822 0.004773 **
date11-19    0.0490311  0.0182370    2.689 0.007176 **
date11-20    0.0821689  0.0181582    4.525 6.03e-06 ***
date11-21    0.0281145  0.0182905    1.537 0.124265
date11-22   -0.0421312  0.0184959   -2.278 0.022735 *
date11-23   -0.0186499  0.0184205   -1.012 0.311321
date11-24   -0.0807009  0.0186224   -4.334 1.47e-05 ***
date11-25   -0.0805769  0.0186053   -4.331 1.49e-05 ***
date11-26   -0.0263293  0.0184438   -1.428 0.153424
date11-27   -0.0649564  0.0185641   -3.499 0.000467 ***
date11-28   -0.0447237  0.0184933   -2.418 0.015590 *
date11-29   -0.0029373  0.0183853   -0.160 0.873065
date11-30           NA         NA       NA       NA
date12-01    0.2442484  0.0190817   12.800  < 2e-16 ***
date12-02    0.2348288  0.0190964   12.297  < 2e-16 ***
date12-03    0.2343583  0.0190885   12.277  < 2e-16 ***
date12-04    0.1957897  0.0192056   10.194  < 2e-16 ***
date12-05    0.1983939  0.0191858   10.341  < 2e-16 ***
date12-06    0.2043113  0.0191780   10.653  < 2e-16 ***
date12-07    0.1792156  0.0192426    9.313  < 2e-16 ***
date12-08    0.1701283  0.0192849    8.822  < 2e-16 ***
date12-09    0.1586196  0.0193066    8.216  < 2e-16 ***
date12-10    0.1948727  0.0191956   10.152  < 2e-16 ***
date12-11    0.1764144  0.0192595    9.160  < 2e-16 ***
date12-12    0.2177888  0.0191330   11.383  < 2e-16 ***
date12-13    0.2173455  0.0191425   11.354  < 2e-16 ***
date12-14    0.2244384  0.0191187   11.739  < 2e-16 ***
date12-15    0.2252111  0.0191327   11.771  < 2e-16 ***
date12-16    0.1670190  0.0192828    8.662  < 2e-16 ***
date12-17    0.1884187  0.0192135    9.807  < 2e-16 ***
date12-18    0.1521362  0.0193283    7.871 3.51e-15 ***
date12-19    0.1726605  0.0192572    8.966  < 2e-16 ***
date12-20    0.1966517  0.0191990   10.243  < 2e-16 ***
date12-21    0.1719574  0.0192629    8.927  < 2e-16 ***
date12-22    0.1560308  0.0193250    8.074 6.80e-16 ***
date12-23    0.1258770  0.0194010    6.488 8.69e-11 ***
date12-24   -0.1184178  0.0201790   -5.868 4.40e-09 ***
date12-25   -0.4663420  0.0216173  -21.573  < 2e-16 ***
date12-26   -0.0257413  0.0198607   -1.296 0.194943
date12-27    0.1095159  0.0194477    5.631 1.79e-08 ***
date12-28    0.1362303  0.0193646    7.035 1.99e-12 ***
date12-29    0.1271107  0.0194087    6.549 5.79e-11 ***
date12-30    0.1279582  0.0193949    6.598 4.18e-11 ***
date12-31           NA         NA       NA       NA
year2002     0.0012870  0.0034914    0.369 0.712408
year2003    -0.0149848  0.0034990   -4.283 1.85e-05 ***
```

```
year2004    -0.2255043  0.0036052  -62.550  < 2e-16 ***
year2005    -0.0560175  0.0035186  -15.920  < 2e-16 ***
year2006    -0.0686682  0.0035249  -19.481  < 2e-16 ***
year2007    -0.1123322  0.0035467  -31.672  < 2e-16 ***
year2008    -0.1510335  0.0035650  -42.365  < 2e-16 ***
year2009    -0.2366193  0.0036134  -65.484  < 2e-16 ***
year2010    -0.2856600  0.0036415  -78.446  < 2e-16 ***
year2011    -0.3507063  0.0036807  -95.282  < 2e-16 ***
year2012    -0.3964367  0.0037076 -106.926  < 2e-16 ***
year2013    -0.4973884  0.0037769 -131.693  < 2e-16 ***
year2014    -0.6148876  0.0038624 -159.199  < 2e-16 ***
year2015    -0.6618549  0.0038989 -169.756  < 2e-16 ***
year2016    -0.6694555  0.0039023 -171.556  < 2e-16 ***
year2017    -0.7400986  0.0151023  -49.006  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(23.2408) family taken to be 1)

Null deviance: 882624  on 257927  degrees of freedom
Residual deviance: 279248  on 257518  degrees of freedom
AIC: 1535857

Number of Fisher Scoring iterations: 1


Theta:  23.241
Std. Err.:  0.171

2 x log-likelihood:  -1535034.510
```

Note that for 11 levels of “`date`”, coefficients were not defined. This is likely due to collinearity with the “`month`” variable. Only “`month`” was used in the model used for simulations, therefore this can be disregarded.

Appendix 5: Best-subset Analysis Output

Best-subset Analysis R Output.

```
AIC
Best Model:
                Df   Sum Sq Mean Sq   F value Pr(>F)    
district        21  5051384  240542   5496.53 <2e-16 ***
date           365   846192    2318     52.98 <2e-16 ***
hour_of_day      1  6316707 6316707 144340.47 <2e-16 ***
day_of_week      6    67598   11266    257.44 <2e-16 ***
Residuals   257534 11270345      44                     
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Table A1. Output of “`bestglm()`” function from the R “`bestglm`” package for the Negative Binomial regression model using “half-day” timepoint resolution.

Appendix 6: Distribution Comparisons

Proof that a Poisson distribution is more suitable that a Negative Binomial distribution for modelling crime count distribution for a given timepoint and district, for the purpose of sampling during simulations (**Figure A3**), as well as demonstration of similarity between training dataset crime count distribution with simulated next year crime count distribution (**Figures A4** & **A5**).

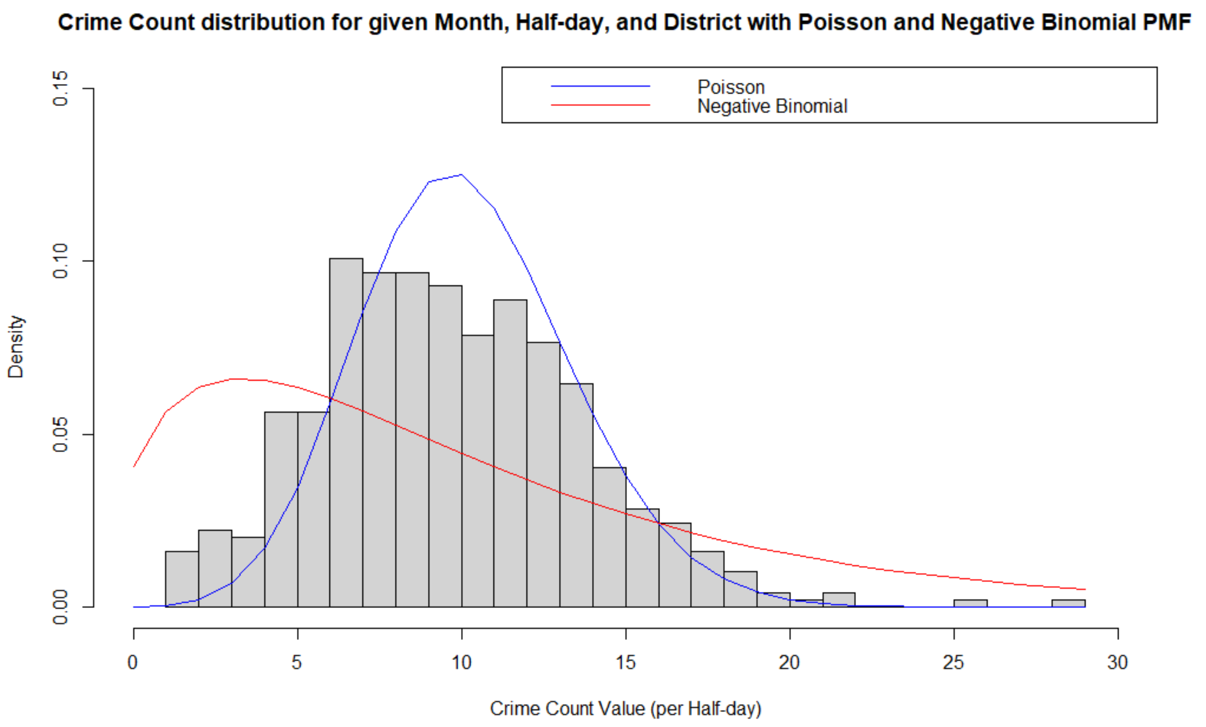

Figure A3. Crime Count distribution for given Month (May), Half-day (first half), and District (5) with Poisson and Negative Binomial PMF. Crime counts for each day in a given month were taken across all years so as to maximize sample size. As a result, dispersion here might be higher than in reality, as the effects of year and weekday will be felt on the data in this sample, whereas when sampling an exact timepoint, these will be kept equal.

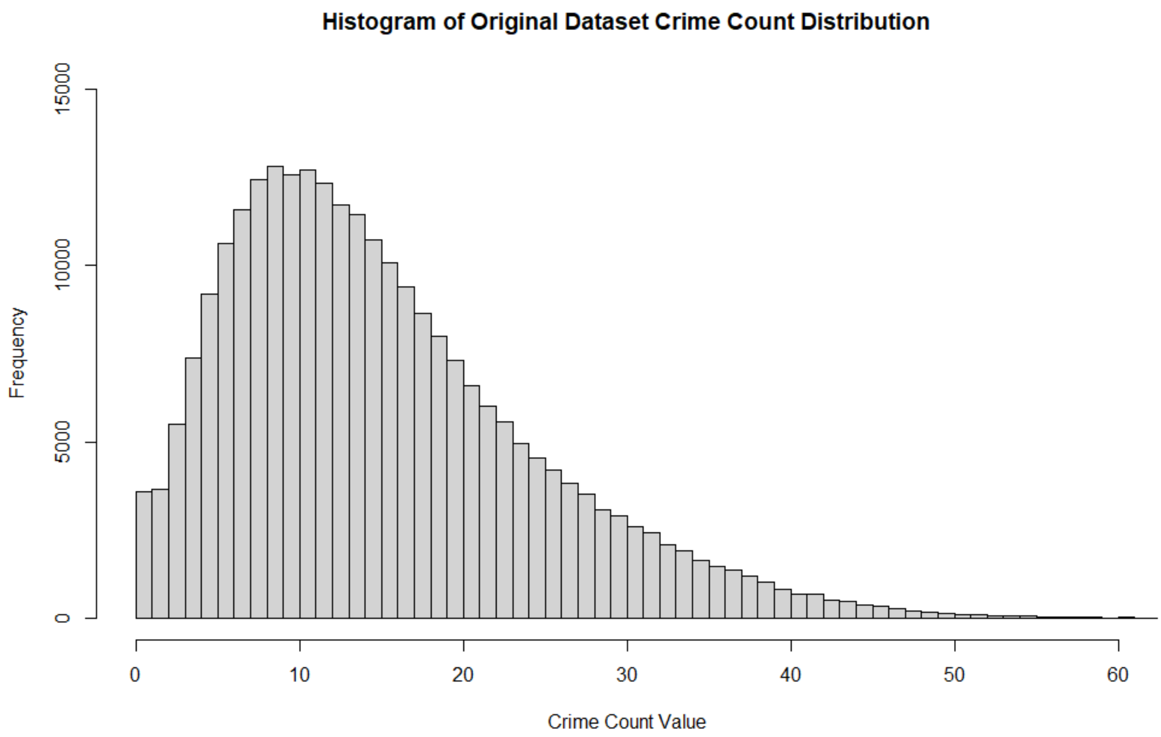

Figure A4. Histogram of Original Dataset Crime Count Distribution.

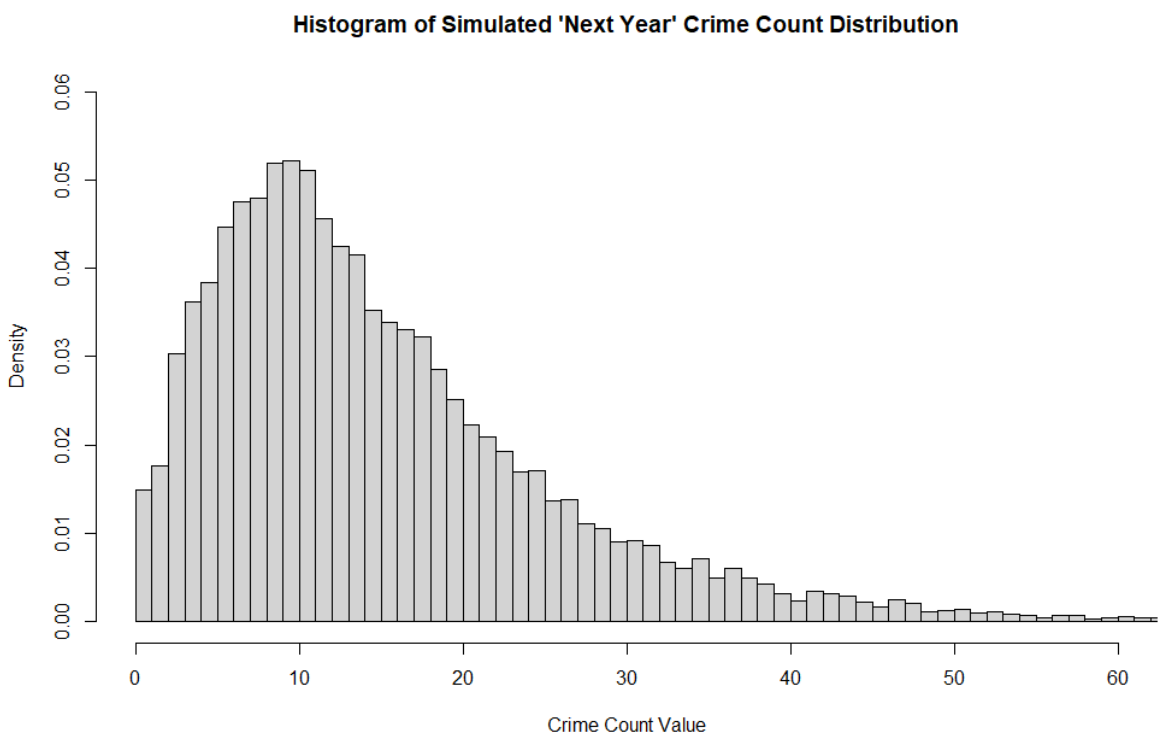

Figure A5. Histogram of Simulated 'Next Year' Crime Count Distribution. Greater stochasticity observed due to it only being one year's worth of data (n = 16, 060) compared to over 16 years (n = 257,928). Note that there is an additional peak around the count value of 13. This quasi-bimodality might be an effect of grouping hour timepoints into half-day timepoints; this results in a new variable with just two levels, between which the difference in effect on crime count is great. This condition is conducive to the emergence of bimodality in a dataset. Additionally, the grouping of days into months might contribute a similar effect. This effect of simulations is one that occurs as a trade-off of the aforementioned aggregation of variable levels. However, it is assumed that the effect on simulated distributions between districts will be equal, therefore this should not affect the outcome of simulations with regard to what is being investigated.

Original Dataset	Next Year Simulation (5 reps)
Mean = 15.599	Mean = 15.559 (15.502, 15.585, 15.534, 15.566, 15.607)
Mode = 9	Mode = 8, 10, 8, 8, 10
Median = 14	Median = 13, 13, 13, 13, 13

No significant difference between means (two-sided T-test, P = 0.578). Modes seem far apart, but looking at the graph, there's not much in it.

Appendix 7: Checking Z-score Normality Assumption

Checking assumption of normality for generation of Z-scores.

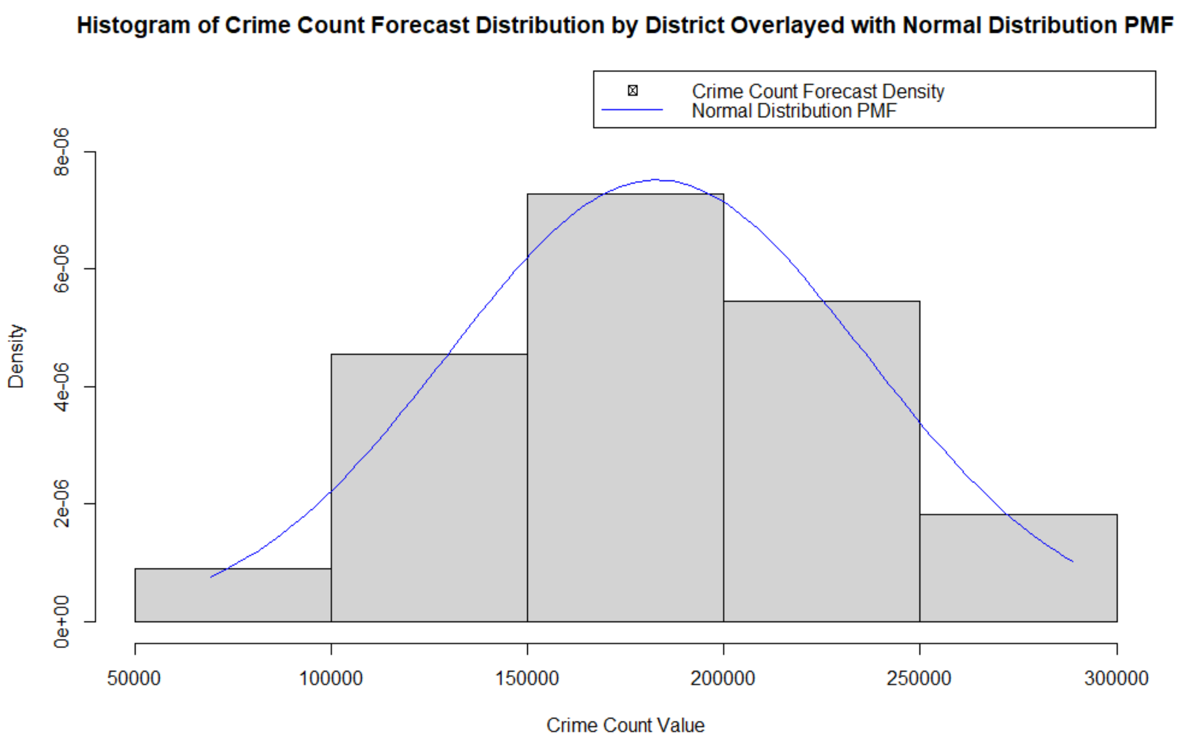

Figure A6. Histogram of Crime Count Forecast Distribution by District Overlayed with Normal Distribution PMF. Forecast is of a year with no additional parameters set.