THE UNIVERSITY OF CHICAGO

# A Quantitative Analysis on Impact of Facial Recognition Technology on Chicago Crime 2013

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**Abstract**

The use of facial recognition technologies by the Chicago Police Department (CPD) has sparked many controversies over its ethicality and efficacy in fighting crime. Main arguments in the debate of whether to use facial recognition technology in policy come from data privacy issues and flaws in existing technologies to correctly identify faces. This thesis contributes to the discussion by bringing tangible data insights from historical Chicago crime data, specifically after the implementation of DataWorks Plus's facial recognition technologies in 2013. A negative correlation between motor vehicle theft and use of facial recognition technology was found, however no correlation was found for the other types of crimes examined: arson, assault, criminal damages, homicide, robbery, sex offense, theft. Based on the lack of impact on violent or private crimes, and valid concerns over algorithmic bias, this thesis recommends limiting the police use of facial recognition software to non-violent crimes and reviewing city data retention policies for video surveillance footage.

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## I. Introduction

Personal identification in the context of felonies can be an arduous task. Police rely on witness testimonies and leverage unique physical identifiers like fingerprint and DNA evidence to narrow a large pool of suspects to single individuals. With eyewitnesses, police may decide to assess the accuracy of the witness account by assembling a line-up of innocent people with the suspect, then requesting the witness to identify the suspect–a process that takes time and coordination with several people. With biological identifiers, a clear fingerprint or uncontaminated DNA evidence can be hard to obtain, not to mention the cost and time necessary to perform laboratory analysis. These tools for identifying people are resource and time intensive, pressuring law enforcement to allocate their budget for these tools only to the most serious cases. In comparison, facial recognition technology, in theory, is capable of identifying people at a more efficient rate and requires substantially less manual labor by leveraging 20th century technology.

The ubiquity of cameras in our daily lives has proliferated the amount of useful imaging data that can be collected for building human identification tools. Photo IDs, security cameras, and mobile devices are all sources for capturing human faces that can be used to train machine learning models. Given a database of labeled face data, the machine learning model can develop an identification algorithm of a unique set of traits for each person's face and run the algorithm to match a name to a new face image with a degree of confidence. The identification algorithm will differ between companies, as it is their proprietary product, but in general developing a machine learning algorithm for facial recognition requires accurately labeled imaging data, data cleaning, and a method for translating an image into numeric data.

The use of facial recognition by law enforcement has stirred controversies regarding an individual's right to privacy and undisclosed use of their data without expressed consent. Historically, the FBI and local law enforcement agencies collect and build a biometric database of DNA data and fingerprints of convicted felons and criminal investigations. Many modern facial recognition models used by police use a larger database of Americans in general, by relying on driver's license photos for their labeled data. The ethicality of using this data without expressed consent has led to lawsuits and bans on city and state use of facial recognition in specific contexts.

While recognizing the ethical argument to banning the use of facial recognition in policing, this thesis will focus on quantifying objective effects of facial recognition through changes in Chicago's crime statistics before, during, and after the use of commercial facial recognition software. As private companies have their own approaches for tackling each of these three requirements for their facial recognition product, this thesis will specifically analyze the partnership between the Chicago Police Department (CPD) and the commercial facial recognition company, DataWorks Plus. In 2013, the CPD worked with DataWorks Plus through a contract deal with Motorola until 2015, and has renewed their partnership annually since[1].

In May of 2020, the CPD abruptly ended a pilot program with another commercial facial recognition company, Clearview AI, as the ACLU sued the technology company and pressured the CPD to stop the use of facial recognition technologies in policing[2]. As a result, in recent years, the topic of using facial recognition in technology has been a controversial one, where

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[1] DataWorks Plus. "DataWorks Plus," n.d. http://www.dataworksplus.com/about.html.

[2] Clare Garvie, Alvaro M. Bedoya, and Jonathan Frankle. "The Perpetual Line-Up: Unregulated Police Face Recognition In America." Georgetown Law: Center on Privacy & Technology, n.d. https://www.perpetuallineup.org/sites/default/files/2016-12/The%20Perpetual%20Line-Up%20-%20Center%20on%20Privacy%20and%20Technology%20at%20Georgetown%20Law%20-%20121616.pdf.

both sides–those who support the use and those who are against the use–hold firm beliefs in the efficacy and effectiveness of its use in reducing crime.

This thesis will contribute to this discussion by providing objective, quantitative data about any differences in crime rates or changes in crime rate trends after CPD's partnership with DataWorks Plus in 2013, in an attempt to assess the efficacy of using facial recognition software in reducing crime. By identifying any significant changes in crime rate trends, and compartmentalizing the analysis for different types of crime, I can evaluate the appropriateness of using facial recognition for specific policing functions and provide areas for continued research for policy recommendations.

## I. Background

The idea of utilizing biometric data in the business and government sectors took off in the late 1960s as an avenue for providing security to computer networks but also surveillance in the external world (Gates 2011). The Department of Defense and intelligence agencies funded research labs to learn how to program computers to identify human faces, and by the 1990s, private companies were formed that commercialized the technology for markets that require large-scale identification systems. These markets include banking and consumer research industries, which played a significant role in generating demand for biometric identification. The potential applications for biometric identification was endlessly versatile and valuable– employers could naturally track their personnel with a unique identifier. Face image data promised relative advantages over other biometric features, namely its lack of a criminal connotation which fingerprints were associated with, a massive existing archive of data to use as nearly everyone has photo ID, and an integration with video surveillance to allow for stealthy identification from a distance.

While the government subsidized research, it was the private technology sector that applied and funded the migration of facial recognition algorithms from computer labs to real-world products. This timeline for the development of mature facial recognition explains one element of the contracting relationship between government agencies and their contracted private companies that now exists today. Another element of the public sphere's reliance on private companies for facial recognition technology is the intrinsic difficulty of developing a technical biometric standard for accurate facial recognitions. The effort necessary to develop a rigorous enough standard for the government to accept is beyond the capacity of governments with their limited budget and overflowing responsibilities. As a result, while the interest in leveraging facial recognition has only increased over time as its applicative capabilities grew clearer, institutional standardization and policies regulating applications of facial recognition lagged behind. Government law enforcement agencies that now contract with private companies to use their facial recognition software experimentally and with optimism that these new tools will allow them to improve their ability to identify felons.

While facial recognition technology and strategies in criminal policing are well explored research topics in the last several decades, examining the integration of the two has only exploded and gained public attention in the last year. This relatively new topic of facial recognition technology used by local government police departments has caught the ire of interest groups determined to preserve the privacy of law-abiding individuals in society, stirring conversations on the ethics of using a currently unperfected technology for law enforcement. Existing research in the field has aimed to attack or defend the use of facial recognition in policing by constructing ethical cases and defining rates of accuracy across different demographics in the lab.

It's worth noting that face recognition technologies are not inherently built with algorithmic biases for specific racial groups. The Face Recognition Vendor Test (FRVT) performed by the National Institute of Standards and Technology explains it clearly[3]:

> *"Face recognition algorithms, however, have no built-in notion of a particular person. They are not built to identify particular people; instead they include a face detector followed by a feature extraction algorithm that converts one or more images of a person into a vector of values that relate to the identity of the person… algorithms compare two*

[3] Patrick Grother, Mei Ngan, Kayee Hanaoka. "Face Recognition Vendor Test (FRVT) Part 3: Demographic Effects." National Institute of Standards and Technology, December 2019. https://nvlpubs.nist.gov/nistpubs/ir/2019/NIST.IR.8280.pdf.

*feature vectors and emit a similarity score. This is a vendor-defined numeric value expressing how similar the parent faces are. It is compared to a threshold value to decide whether two samples are from, or represent, the same person or not. Thus, recognition is mediated by persistent identity information stored in a feature vector (or "template")."*

Therefore, algorithmic bias in the end product generally comes from improper training data for the algorithms and human misuse of the technology. If the training data disproportionately represent one race over another, the race with greater representation in the dataset will be identified with greater accuracy than the identification of a minority race. From FRVT, this is apparent in algorithms they have tested in both Western and Eastern countries, where the algorithms sourced from the United States generally had higher rates of false positive[4] identifications for black women than white men, and the algorithms sourced from China had higher rates of misidentification for European faces than for East Asian faces. Regarding human misuse of the technology, operational implementation of face recognition algorithms–specifically the interface for police officers to interact with the facial recognition technology–may unintentionally influence human decision-making.

**DataWorks Plus Commercial Facial Recognition**

There are several big players in the space of private facial recognition companies in the United States and government agencies have become a major client for their work. DataWorks Plus is one such company, providing a wide-range of technology solutions for law enforcement,

[4] False positives are the erroneous association of samples of two persons; they occur when the digitized faces of two people are similar.

criminal justice, and government agencies since 20005. According to the company website, their product offerings include facial recognition case management as of 2005, which consists of facial image database searches, 3D facial rendering and recognition, facial recognition from still images, and facial recognition video screening and analytics.

Of the services DataWorks Plus provides, the Chicago Police Department and Chicago Transit Authority are using the real time recognition system on Chicago's security camera network, which includes approximately 20,000 video cameras. As of February 2021, the DataWorks Plus website listed Chicago as one of their past clients for their "FACE Watch Plus" product in 2013. Their system includes 7 million criminal photos and states they use "the system primarily to solve crimes using probes generated from street cameras, Facebook, and other sources." As of April 2021, this page can no longer be found on their website.

[5] DataWorks Plus. "DataWorks Plus," n.d. http://www.dataworksplus.com/about.html.

## II. Literature Review

### Public Support for Facial Recognition via Police Body-Worn Cameras

Bromberg (2020) examined the public support for facial recognition from policy body-worn cameras in a sample of residents in New Hampshire[6]. Researchers tested social norms for the adoption of facial recognition technology based on an experiment with a sample of residents of New Hampshire through a phone survey, and with a sample of Americans through a web survey. The experiment uncovered results that reveal how gender, age and political affiliation matters to explain support for facial recognition, as women and non-Trump voters harbor reticence that they only express when provided with a measure of anonymity. Through anonymous phone surveys, they discovered how demographics mattered in defining the likelihood of supporting body-worn cameras.

### A Data-Driven Framework Towards Fair and High Performing Facial Recognition Systems

Cao and Berend (2020) evaluated the performance and fairness of age prediction algorithms in facial recognition from industrial service providers, Amazon AWS and Microsoft Azure[7]. After identifying characteristics that led to unfair detections towards certain ethnicities

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[6] Bromberg, Daniel E., Étienne Charbonneau, and Andrew Smith. "Public Support for Facial Recognition via Police Body-Worn Cameras: Findings from a List Experiment." *Government Information Quarterly* 37, no. 1 (January 1, 2020). http://proxy.uchicago.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=edselp&AN=S0740624X19300449&site=eds-live&scope=site.

[7] Cao, Yushi, David Berend, Palina Tolmach, Moshe Levy, Guy Amit, Asaf Shabtai, Yuval Elovici, and Yang Liu. "Fairness Matters -- A Data-Driven Framework Towards Fair and High Performing Facial Recognition Systems," 2020. http://proxy.uchicago.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=edsarx&AN=edsarx.2009.05283&site=eds-live&scope=site.

and genders when predicting age, Cao and Berend proposed a new methodology that augments on the training set dataset curation process for a better distribution-aware algorithm that reduces the absolute age prediction error substantially.

**Political-Economy Analysis of the Provision of Urban Anti-Crime Technologies**

Batabyal (2020) presented a political-economy model for measuring the cost, benefit, and spatial spillover terms of using contentious crime fighting technologies, such as facial recognition software[8]. In particular, Batabyal emphasized the consideration of monitoring traffic flows and monetizing the cost-benefit to determine whether there is net benefit from using anti-crime technology.

This research will utilize the conclusions from Batabyal's paper and extend on the theoretical examinations of facial recognition in the lab in the context of its real-world application. Results from facial recognition accuracy research performed by the National Institute of Standards and Technology (NIST) and the U.S. Government Accountability Office (GAO) do not fully measure changes in crime statistics that may occur when the same technologies are used by local law enforcement. Factors like public sentiment from knowledge of facial recognition technologies being used by police officers may also contribute to reduced crime. While not caused by the facial recognition algorithm, this research intends to encapsulate these kinds of effects that cannot be simulated in a lab environment when analyzing the quantitative effects of using facial recognition in policing.

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[8] Batabyal, Amitrajeet A., Karima Kourtit, and Peter Nijkamp. "A Political-Economy Analysis of the Provision of Urban Anti-Crime Technologies in a Model with Three Cities." *Technological Forecasting & Social Change* 160 (November 1, 2020). http://proxy.uchicago.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=edselp&AN=S0040162520310374&site=eds-live&scope=site.

## III. Methods

For analyzing the effect of implementing facial recognition in Chicago's policing, this thesis will be using two methods: a difference-in-differences (DID) method by comparing the crime data in Milwaukee and the crime data in Chicago, and a forecasted approach of predicting Chicago's crime data at the start of when Chicago started using facial recognition and comparing the forecasted crime data with actual crime data. Both methods aim to identify whether the real-world Chicago crime data is statistically significant from the treatment control group, but the first method uses Milwaukee as a control and the second method uses Chicago as its own control. Identifying common trends in both methods would strengthen the conclusions we are able to make on quantitative effects of using facial recognition technologies on reported crime rates. Furthermore, the unavailability of a post-treatment study for the DID design makes supplementing the conclusions from DID with another method necessary rather than redundant. The legitimacy of the DID results can also be strengthened with the addition of other valid control treatment groups for Chicago, which can be explored further in expansion to this thesis.

The data used in both methods are Milwaukee's and Chicago's public crime data. The city of Milwaukee supplies crime data with incident levels defined by Wisconsin Incident Based Reporting System (WIBRS) codes, and updated frequently on a near daily basis. Chicago's open data portal contains a well-maintained dataset of reported crime from 2001 to present day, excluding murder and incidents that transpired within the most recent 7 days. Data is sourced from the Chicago Police Department's CLEAR (Citizen Law Enforcement Analysis and Reporting) system. CLEAR is a relational database used by the CPD to store comprehensive information about approximately ten million crime reports. While Milwaukee's and Chicago's crime datasets differ slightly in details of what is reported, the aggregate of information is labelled similarly enough that there is a wealth of information that can be compared for the first experimental method of using DID.

The prediction for using both methods and separating by types of crime are that we are unlikely to find significant changes or decreases in crime rates for non-public and violent types of crime. This would make sense because of the lack of cameras that would capture those crimes, like sex offense, and the fact that violent crimes will already be heavily scrutinized over that adding facial recognition will do little to increase the effort already feeding into resolving violent crimes like homicide.

**Difference-in-Differences with Milwaukee**

The difference-in-differences experimental design, using Milwaukee as the control group, was selected for the similarities between the city of Milwaukee and the city of Chicago and Milwaukee's distinct stance *against* using facial recognition technologies in policing[9]. Potential demographic factors that affect crime rates across types of crime that were considered include age, race, family, and political distribution–all of which the two cities are very similar in, relative to the United States' average[10]. Police-specific characteristics were also considered, including the police budget per capita in 2013 for both cities: $0.46 for Chicago and $1.36 for Milwaukee, both in the same order of magnitude[11][12].

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[9] Clare Garvie, Alvaro M. Bedoya, and Jonathan Frankle. "The Perpetual Line-Up: Unregulated Police Face Recognition In America." Georgetown Law: Center on Privacy & Technology, n.d. https://www.perpetuallineup.org/sites/default/files/2016-12/The%20Perpetual%20Line-Up%20-%20Center%20on%20Privacy%20and%20Technology%20at%20Georgetown%20Law%20-%20121616.pdf.

[10] *2021 Compare Cities People: Milwaukee, WI vs Chicago, IL*. BestPlaces, n.d. https://www.bestplaces.net/compare-cities/milwaukee_wi/chicago_il/people.

[11] Susana A. Mendoza. "Annual Appropriation Ordinance For The Year 2013," 2013. https://chicityclerk.s3.amazonaws.com/s3fs-public/document_uploads/budget/2013/Annual-Appropriation-Ordinance-2013.pdf.,

[12] Sharon Robinson, Mark Nicolini. "2013 Plan And Budget Summary: City Of Milwaukee." Budget

The design difference-in-differences method uses 2012 crime data for both cities to test for pre-treatment effect, and 2013 crime data for post-treatment effect since the contract with DataWorks Plus was effective as of the beginning of 2013. Each type of crime was evaluated separately when measuring the difference in differences of crime rates between Chicago and Milwaukee in 2012 and 2013. The types of crime that were evaluated were arson, assault, criminal damages, homicide, robbery, sex offense, theft, and motor vehicle theft.

For the pre-test, I look at crime rates for each type of crime in 2012, and for the post onset of the treatment, I look at the respective crime rates in 2013. Using Milwaukee crime data as my control variable, I identify whether a change in crimes rates for a particular type of crime from 2012 to 2013 in Chicago was significantly different from the change in respective crime rate in Milwaukee. Considering the treatment effect started in the beginning of 2013, if the facial recognition technologies adopted from DataWorks Plus actually helped with reducing crime rates, we would expect to see statistically significant results later in the year of 2013, as police officers familiarized themselves with the technology and had the time to put their findings to use.

To test for statistical significance in Chicago's change in crime, I compute the z-score of each difference in difference in crime rate for each type of crime for each month of the year. I choose to aggregate crime counts by month due to the seasonality of crime as identified in my earlier analysis where I found consistent spikes in historical crime data for both Chicago and Milwaukee. To compute the z-score, I compare the Milwaukee-Chicago differences in change in crime rates from 2012 to 2013 to the historical mean and standard deviation in differences in annual change of crime rates of each month in Microsoft Excel. Using the z-score, I am then able

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And Management Division, 2013. https://city.milwaukee.gov/ImageLibrary/User/crystali/Budget-_Books/2013BudgetSummary.pdf.

to compute a p-value and observe the probability of obtaining test results as extreme as the difference observe to understand whether there is a statistically significant change in crime in Chicago in 2013. A statistically significant decrease in crime rate would support the idea that an event or phenomenon in 2013 impacted crime rates, rather than the change in crime rates occurring randomly.

**Facebook Prophet's Additive Forecasting Model for Non-Linear Trends**

The method of finding differences between predicted crime rates and actual measured crime rates can be labeled as a changes-in-changes (CIC) model where a counterfactual outcome is derived from modular regression of historical crime data by ending the historical input data at the time of the treatment. The particular regression used in this thesis is a generalized additive model $y(t) = g(t) + s(t) + h(t) + \varepsilon_t$, which is a class of regression models with non-linear smoothers, encapsulating year-to-year, annual, seasonal, monthly, and holiday patterns in crime rates, applied to the regressors. Growth is modeled with a logistic growth model originally built from the sklearn library, designed for forecasting time-series data. Using Chicago crime data from 2005 to the end of 2012, I predict the crime rates for each type of crime listed earlier for the next three years, with focus on the predicted crime rates in 2013 and 2014 to capture the immediate saliency of introducing mass facial recognition technologies in Chicago policing behavior.

What this method allows us to achieve is extrapolation of any crime trends in Chicago–whether they may come from natural occurring effects of the changing economy, increase in climate change, or passing of more progressive policies–into the future without the laborious and impossible task of identifying each possible trend. By having the end of 2012 as our cut-off point, I am able to exclude any effects that may arise from using facial recognition technologies in the crime data predictions. Compared to the difference-in-differences design, instead of using Milwaukee as a control city, the predicted crime rates in 2013 to 2015 become the control that we compare the same years of Chicago crime rates to. The use of historical crime data provides trends specific to Chicago in our analysis, supplementing the DID analysis which allowed us to control for how events in 2013 in general may have contributed to crime. The combination of both methods gives greater credibility to any common finding resulted from each individual method.

The software used to perform this forecasting is called Prophet, an open source forecasting procedure released by Facebook's Core Data Science team that is implemented in R and Python[13]. This procedure implements two trend models that are also relevant to the kind of trend patterns previously found in Chicago crime data. The first is a saturating growth model, which is relevant to the non-monotonic behavior of criminal events with respect to size of population[14] and the overall steady decline of crime in the past two decades[15]. Prophet's growth forecasting considers nonlinear growth that saturates at a carrying capacity using a logistic growth model. The second is a piece-wise growth model, for handling cases that do not have saturating growth. This is relevant to crime data when recognizing how specific events at specific points in time can have an immediate impact on certain crime rates.

Therefore, the advantage of this prediction method is that it is able to handle non-linear data with seasonality. For instance, crime varies specifically based on the month of the year with

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[13] Taylor SJ, Letham B. 2017. Forecasting at scale. PeerJ Preprints 5:e3190v2 https://doi.org/10.7287/peerj.preprints.3190v2

[14] Fonoberova, Maria, Fonoberov, Vladimir A., Mezic, Igor, Mezic, Jadranka and Brantingham, P. Jeffrey. "Nonlinear Dynamics of Crime and Violence in Urban Settings" 15 http://jasss.soc.surrey.ac.uk/15/1/2.html.

[15] Papachristos, Andrew V. "48 YEARS OF CRIME IN CHICAGO: A Descriptive Analysis of Serious Crime Trends from 1965 to 2013." Yale ISPS, 2013. https://www.bpichicago.org/wp-content/uploads/2014/04/48yearsOfcrime_final_ISPSWorkingPaper023.pdf.

annual spikes around December. The accuracy of this method was first tested with Milwaukee data. Appendix Table 22 contain examples of two graphs generated using historical crime data from Milwaukee from 2006 to 2013 for theft and motor vehicle theft rates. The solid blue line is predictive and extends past 2013 to forecast crime rates for the given type of crime. This preliminary test for method accuracy revealed a high accuracy for predictions, as the forecasted crime rates for the types of crimes tested all fell within 95% confidence interval, and closer to the predicted value than the end of the predicted ranges. The seasonality of Milwaukee crime patterns across the years, days of the week, months in the year, can be observed in Appendix Table 23. The y-axis measures counts of crime and the x-axis measures time.

**Qualitative Research for Confounder Events**

After identifying any significant decreases in crime rates for specific types of crime using the two methods above, I look for any Chicago policing policies and high-visibility events in the year that may also have contributed to the decrease in crime rates. To identify potential events that may have also impacted the specific significant trends identified across crime types, I targeted the search specifically to journalistic pieces that discuss the fall in crime rates in 2013, as well as examine the legislation passed in the city of Chicago in online legislation records. While this is not a fool-proof method for identifying other sources of impact on crime, it will allow me to have a granular, date-specific view of any major Chicago events that could seriously call into question any strong time-dependent findings from the DID and CIC methods. Ultimately, the combination of quantitative and qualitative research methods create a more comprehensive and realistic assessment of facial recognition technology impact on Chicago crime in 2013.

## IV. Data and Analysis

### Analysis of Difference-in-Differences with Milwaukee

When evaluating the statistical significance of these differences using a 95% confidence interval, the types of crimes with *insignificant* change in difference in crime rates between Milwaukee and Chicago consistently throughout the months of 2012 and 2013 were arson, assault, criminal damage, homicide, robbery, sex offense, and theft (see Tables 1-7). This makes motor vehicle theft the only category of crime with statistically significant difference in difference crime rate from before Chicago began using facial recognition technology with DataWork Plus and after Chicago began using facial recognition technology with DataWork Plus (see Table 8a).

For motor vehicle thefts since March, the change in difference in crime rates between Chicago and Milwaukee is consistently statistically significant, with a p-value of less than 0.05. Chicago experienced a significant growing decrease in motor vehicle thefts, with an average decrease of 30.3% since the previous year, in terms of difference between Chicago and Milwaukee motor vehicle theft rates (see Table 8b). The idea that facial recognition technologies may have decreased motor vehicle thefts is plausible because of the public nature of the crime with surveillance cameras and greater possibility of repeat offenders relative to other types of crimes. In 2012, the change in motor vehicle theft rates in Chicago mirrored the change in theft rates in Milwaukee much more closely than the motor vehicle theft rates in 2013, when Chicago experienced steady decline in motor vehicle thefts as the year went on.

**Analysis of Predicted Crime Data Using Additive Forecasting Model**

Using this method of comparing forecasted crime rates using Chicago crime data dating from 2005 to 2013 to predict crime rates from 2013 to 2015, returned predicted crime rates for each type of crime and a 95% confidence interval range for each prediction (see Tables 24-29 for graphs). Statistical significance test using z-scores was done on each of the difference in crime rates and difference in changes in crime rates (see Tables 9-24). There was no statistical significance in difference in changes in crime rates for any of the types of crime, using a p-value of 0.05. However, there were statistically significant results for criminal damage, theft, and robbery in 2014, and sex offense and motor vehicle theft for 2013 and 2014. Most notable of the results is the very statistically significant decrease in rate of motor vehicle thefts from 2013 to 2014, when normalized. When fitted, the slope of the regression is -371.2ln(x).

When combining the data analysis results from both methods, we find a seemingly insignificant effect of using facial recognition in the immediate two years on most types of crime. However, the types of crimes that had the greatest decreases beginning in 2013 are exactly like the ones predicted: crimes that *are* public and *not* violent. Namely, motor vehicle thefts reduced significantly, as well as criminal damage, robbery, and theft in 2014.

It's reasonable to consider the possibility that these results are actually due to increased camera use by the Chicago Police Department, rather than actually due to use of facial recognition software. However, previous research by the Urban Institute Justice Policy Center published in 2011 reveal that increase security cameras do not actually reduce crime rates[16]. Further investigation will be necessary to see if this is in the case with Chicago by examining

[16] La Vigne, Nancy, Samantha S. Lowry, Joshua A. Markman, and Allison M. Dwyer. "Evaluating the Use of Public Surveillance Cameras for Crime Control and Prevention." Urban Institute: Justice Policy Center, September 2011. https://www.urban.org/sites/default/files/publication/27556/412403-evaluating-the-use-of-public-surveillance-cameras-for-crime-control-and-prevention_1.pdf.

other instances of increased security cameras placed in the city to see if similar correlations occur.

**Looking for Potential Confounders**

As the manual qualitative portion of this thesis's investigation of facial recognition technology's impact on crime rates in Chicago, I turned to identifying any local legislation or high-visibility current events that may have also caused a significant decrease in motor vehicle thefts–the only type of crime from Chicago Police Department data with statistically significant crime rate changes in 2013. Beginning with political or legislative efforts, I searched for passed legislation regarding crime, vehicles theft, or passed ordinances on the Chicago Office of City Clerk website[17], as well as Journal of the Proceedings[18], which reflects all legislative actions from the city council, from late 2012 to mid 2013. Records that passed, filtered by the keyword "vehicle," from the City Clerk website only displayed individual miscellaneous events, such as damage claims and a few parking ordinances, that are unlikely to contribute significantly, if at all, to crime rates. When searching for more general keywords regarding anti-crime efforts, or ordinances and orders that were passed, nothing relevant appeared that would suggest a new public safety effort that would curb the number of motor vehicle thefts.

This database research suggests, at least from the perspective of legislative city records, there were no targeted efforts on the local level documented in online archives that would have affected motor vehicle theft crime rates. From a national level, in 2013, while the national motor

[17] "Legislative Information Center," n.d. https://chicago.legistar.com/Legislation.aspx.

[18] Office of the City Clerk. "Journals of the Proceedings," n.d. https://www.chicityclerk.com/legislation-records/journals-and-reports/journals-proceedings.

vehicle theft trend was an average drop of 3.9% in crime rate from the previous year, the drop in Chicago was 23% (as calculated from CPD data).

As for the research on high-visibility events in Chicago that may have contributed to the decrease in motor vehicle theft rates, I examined a local archive of notable Chicago news stories in 2013[19]. Among the long list of events, there was one event that stood out as possibly relevant to motor vehicle theft rates: the change to reduced parking meter charges, as well as free Sundays (beginning in the summer of 2013) and pay-by-cell for Chicago parkers on May 8th, 2013[20]. This change was a new settlement agreement announced by previous Mayer Rahm Emanuel between the City of Chicago's finance and legal teams and Chicago Parking Meters (CPM). It's unclear how this improvement in parking policy for Chicagoans could result in a decrease of motor vehicle thefts, since it encourages public parking which would have the opposite effect. In particular, part of the agreement is an extension of metered parking from 10:00pm to midnight, which logically would only increase the range of time for the opportunity of a vehicle theft. Still, regardless of the connection between the passing of this policy and motor vehicle theft rates, the statistically significant decrease in vehicle thefts began in April 2013, before the passing and implementation of this change.

Lastly, it's worth questioning the credibility of the dataset provided by the Chicago Police Department. Questionable behavior from the CPD indicates a possibility that motor vehicle thefts in 2013 were under recorded, especially towards the end of year. Specific cases of

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[19] Smith, Scott. "Chicago 2013: A Year in Review." *Our Man in Chicago*, January 1, 2014. http://www.ourmaninchicago.net/2014/01/chicago-2013-a-year-in-review/.

[20] Mayor's Press Office. "Mayor Emanuel Announces $1 Billion in Reduced Parking Meter Charges, Free Sundays and Pay-By-Cell for Chicago Parkers," April 29, 2013. https://www.chicago.gov/city/en/depts/mayor/press_room/press_releases/2013/april_2013/mayor_emanuel_announces1billioninreducedparkingmeterchargesfrees.html.

well-known homicides that were reported in the news, such as the homicide of Tiara Groves in October 28, was reclassified as a noncriminal death investigation, ultimately reducing the total number of homicides that year by at least 121. The Chicago magazine investigated other missing numbers, and found "dozens of other crimes, including serious felonies such as robberies, burglaries, and assaults, that were misclassified, downgraded to wrist-slap offenses, or made to vanish altogether."[22] It's unclear if this behavior was mostly performed for violent crimes like homicide, or if the police department was under pressure to uniformly airbrush all recorded crime types. Still, the questionable source of the data used in this thesis merits consideration of other valid data sources to back up the findings.

[12,15,16] David Bernstein and Noah Isakson. "The Truth About Chicago's Crime Rates: Part 2." *Chicago Mag*, May 19, 2014. https://www.chicagomag.com/chicago-magazine/june-2014/chicago-crime-statistics/.

## V. Policy Recommendations

In a study performed by the Pew Research Center in 2019, 56% of Americans trust law enforcement to use facial recognition responsibly, however this percentage varies greatly by race and age[23]. While about 60 percent of the responses from white respondents were trustful of law enforcement with the technology, only 43 percent of the responses from black respondents were. 67 percent of respondents over the age of 65 trust law enforcement with using facial recognition technology, compared to 49 percent of respondents ages 18 to 29. However, when asked whether the government "should be able to monitor and track who you are and where you go using your biometric information," 82 percent of all respondents said no. Overall, the results of this survey reveal a slight distrust in the technology being used by law enforcement from minority groups, and negative sentiment towards their own data being used in the system.

Regarding the accuracy of the facial recognition algorithms, DataWorks Plus has reportedly said that they do not formally measure the accuracy or bias of their products. In a study performed by the National Institute of Standards and Technology (NIST) in 2019 examining facial recognition algorithms for algorithmic bias, they evaluated NEC-3, an algorithm from NEC– a Japanese information technology company of which DataWorks Plus sources their algorithms from[24]–and deemed NEC-3 "on many measures, the most accurate [NIST] have evaluated." In the NIST study, they found that false positive differentials were undetectable. This was concluded from their research where searches of Asian, black, white men and women's faces into mixed galleries of mugshot photos resulted in a heat map of uniform

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[23] Harrison, Sarah. "Poll Finds Americans Trust Police Use of Facial Recognition." *Wired*, September 5, 2019. https://www.wired.com/story/poll-americans-trust-police-facial-recognition/.

[24] Kashmir, Hill. "Wrongfully Accused by an Algorithm." *NYTimes*, August 3, 2020. https://www.nytimes.com/2020/06/24/technology/facial-recognition-arrest.html.

median similarity scores across demographic groups. Although this finding makes DataWorks Plus a relatively better option than many other facial recognition suppliers whose algorithms have been found to have salient algorithmic biases from the NIST study, it does not absolve the use of facial recognition technologies from DataWorks Plus from possibly contributing to human cognitive biases.

Combining the ethical concerns described above and the findings from the DID and CIC methods, this thesis recommends limiting the police use of facial recognition software to non-violent crimes and reviewing city data retention policies for video surveillance footage. No significant correlation was found for the onset of using facial recognition technology by the CPD and a decrease in violent crimes, including assault and homicide. Due to the severity of consequences, should results from facial recognition software be used for purposes greater than identifying *potential* suspects in violent crime cases, this thesis suggests only using facial recognition software for, at most, Class 2 felonies, like possession of a stolen motor vehicle. Even for non-violent crimes, it is crucial for police officers using these facial recognition software to recognize potential biases in their data, and receive proper training to operate the software with conscious understanding of how the algorithms operate, so as to not develop or strengthen existing racial biases from potential algorithmic matching patterns.

Due to the fears over privacy and concerns over lack of consent in capturing surveillance data for facial recognition technology use, it is valid to review whether there is truly a necessity in backing up certain surveillance footage for extended periods of time. The Chicago Office of Emergency Management and Communications (OEMC) has no current policy limiting the duration of image retention or requirements for criminal predicate for officers to retrieve and retain camera images at their discretion[25]. Considering these are public surveillance camera images with facial recognition capabilities, there is inherent damage with keeping such sensitive information without reasonable suspicion for fear of possible wrongful use of the data. Since it is not advised to use facial recognition technology for incriminating suspects of violent crimes, the disposal of surveillance data after a relatively short amount of time has little consequence compared to the gain in addressing public mistrust in police misuse of technology.

[25] ACLU of Illinois. “Chicago’s Video Surveillance Cameras: A Pervasive And Unregulated Threat To Our Privacy,” February 2011. https://www.aclu-il.org/sites/default/files/field_documents/video_camera_surveillance_in_chicago.pdf.

## VI. Conclusion

While this thesis found a statistically significant correlation between the onset of using facial recognition technology from DataWorks Plus in Chicago and a subsequent decrease in motor vehicle thefts, more research is necessary to strengthen this connection. I was not able to find any research or statement from the Chicago Police Department to solidify the connection between Chicago's camera systems with facial recognition technology and a decrease in vehicle theft. In the difference-in-differences study and additive forecasting study, no statistically significant change in crime rates for arson, assault, criminal damages, homicide, robbery, sex offense, and theft was found in the year following the onset of facial recognition technology in Chicago policing. Given these findings and ethical studies on public sentiment, as well as the NIST study on the software's potential for perpetuating racial bias, I recommend limiting the police use of facial recognition software to non-violent crimes and reviewing city data retention policies for video surveillance footage.

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## VIII. Appendix

**Table 1. DID for Change in Difference in Crime Rate for Chicago and Milwaukee 2012-2013 [Arson]**

| Month | Difference Between Chicago and Milwaukee 2012 | Difference Between Chicago and Milwaukee 2013 | Change in Difference in Crime Rates 2012-2013 | P-Value |
|---|---|---|---|---|
| Jan | 19 | 18 | -1 | 0.29 |
| Feb | -1 | 15 | 16 | 0.36 |
| Mar | 13 | 6 | -7 | 0.32 |
| Apr | 25 | -3 | -28 | 0.09 |
| May | 8 | 20 | 12 | 0.24 |
| Jun | 1 | 6 | 5 | 0.32 |
| Jul | 16 | -4 | -20 | 0.07 |
| Aug | 21 | -10 | -31 | 0.02 |
| Sep | 11 | -1 | -12 | 0.13 |
| Oct | 10 | -3 | -13 | 0.09 |
| Nov | 0 | -4 | -4 | 0.07 |
| Dec | 14 | 16 | 2 | 0.34 |

**Table 2. DID for Change in Difference in Crime Rate for Chicago and Milwaukee 2012-2013 [Assault]**

| Month | Difference Between Chicago and Milwaukee 2012 | Difference Between Chicago and Milwaukee 2013 | Change in Difference in Crime Rates 2012-2013 | P-Value |
|---|---|---|---|---|
| Jan | 593 | 626 | 33 | 0.17 |
| Feb | 657 | 550 | -107 | 0.09 |
| Mar | 1039 | 578 | -461 | 0.12 |
| Apr | 799 | 752 | -47 | 0.34 |
| May | 1008 | 927 | -81 | 0.36 |
| Jun | 944 | 834 | -110 | 0.40 |
| Jul | 951 | 736 | -215 | 0.32 |
| Aug | 1056 | 734 | -322 | 0.32 |
| Sep | 901 | 829 | -72 | 0.40 |
| Oct | 954 | 759 | -195 | 0.35 |
| Nov | 616 | 545 | -71 | 0.08 |
| Dec | 673 | 441 | -232 | 0.02 |

**Table 3. DID for Change in Difference in Crime Rate for Chicago and Milwaukee 2012-2013 [Criminal Damage]**

| Month | Difference Between Chicago and Milwaukee 2012 | Difference Between Chicago and Milwaukee 2013 | Change in Difference in Crime Rates 2012-2013 | P-Value |
|---|---|---|---|---|
| Jan | 2198 | 2124 | -74 | 0.14 |
| Feb | 1988 | 1646 | -342 | 0.00 |
| Mar | 2667 | 2157 | -510 | 0.16 |
| Apr | 2553 | 2302 | -251 | 0.28 |
| May | 2812 | 2553 | -259 | 0.40 |
| Jun | 3015 | 2399 | -616 | 0.35 |
| Jul | 2933 | 2359 | -574 | 0.32 |
| Aug | 2574 | 2414 | -160 | 0.36 |
| Sep | 2592 | 2245 | -347 | 0.23 |
| Oct | 2560 | 2148 | -412 | 0.16 |
| Nov | 2363 | 2027 | -336 | 0.08 |
| Dec | 2362 | 1761 | -601 | 0.01 |

**Table 4. DID for Change in Difference in Crime Rate for Chicago and Milwaukee 2012-2013 [Homicide]**

| Month | Difference Between Chicago and Milwaukee 2012 | Difference Between Chicago and Milwaukee 2013 | Change in Difference in Crime Rates 2012-2013 | P-Value |
|---|---|---|---|---|
| Jan | 36 | 35 | -1 | 0.40 |
| Feb | 21 | 7 | -14 | 0.01 |
| Mar | 49 | 12 | -37 | 0.04 |
| Apr | 31 | 17 | -14 | 0.09 |
| May | 46 | 43 | -3 | 0.30 |
| Jun | 45 | 37 | -8 | 0.39 |
| Jul | 40 | 38 | -2 | 0.38 |
| Aug | 45 | 30 | -15 | 0.35 |
| Sep | 38 | 29 | -9 | 0.34 |
| Oct | 28 | 24 | -4 | 0.23 |
| Nov | 27 | 19 | -8 | 0.12 |
| Dec | 16 | 32 | 16 | 0.38 |

**Table 5. DID for Change in Difference in Crime Rate for Chicago and Milwaukee 2012-2013 [Robbery]**

| Month | Difference Between Chicago and Milwaukee 2012 | Difference Between Chicago and Milwaukee 2013 | Change in Difference in Crime Rates 2012-2013 | P-Value |
|---|---|---|---|---|
| Jan | 802 | 778 | -24 | 0.34 |
| Feb | 570 | 572 | 2 | 0.06 |
| Mar | 640 | 569 | -71 | 0.06 |
| Apr | 765 | 587 | -178 | 0.07 |
| May | 1021 | 715 | -306 | 0.25 |
| Jun | 1013 | 688 | -325 | 0.20 |
| Jul | 1046 | 872 | -174 | 0.40 |
| Aug | 919 | 757 | -162 | 0.31 |
| Sep | 883 | 769 | -114 | 0.33 |
| Oct | 934 | 714 | -220 | 0.24 |
| Nov | 840 | 656 | -184 | 0.15 |
| Dec | 887 | 786 | -101 | 0.35 |

**Table 6. DID for Change in Difference in Crime Rate for Chicago and Milwaukee 2012-2013 [Sex Offense]**

| Month | Difference Between Chicago and Milwaukee 2012 | Difference Between Chicago and Milwaukee 2013 | Change in Difference in Crime Rates 2012-2013 | P-Value |
|---|---|---|---|---|
| Jan | 68 | 33 | -35 | 0.32 |
| Feb | 11 | 31 | 20 | 0.40 |
| Mar | 35 | 9 | -26 | 0.02 |
| Apr | 15 | 0 | -15 | 0.08 |
| May | 23 | 28 | 5 | 0.29 |
| Jun | 39 | 12 | -27 | 0.02 |
| Jul | 11 | 37 | 26 | 0.38 |
| Aug | 19 | 35 | 16 | 0.39 |
| Sep | 13 | 32 | 19 | 0.40 |
| Oct | 3 | 32 | 29 | 0.36 |
| Nov | -7 | -8 | -1 | 0.22 |
| Dec | 13 | 3 | -10 | 0.12 |

**Table 7. DID for Change in Difference in Crime Rate for Chicago and Milwaukee 2012-2013 [Theft]**

| Month | Difference Between Chicago and Milwaukee 2012 | Difference Between Chicago and Milwaukee 2013 | Change in Difference in Crime Rates 2012-2013 | P-Value |
|---|---|---|---|---|
| Jan | 4886 | 4729 | -157 | 0.22 |
| Feb | 4087 | 3969 | -118 | 0.03 |
| Mar | 4978 | 4601 | -377 | 0.18 |
| Apr | 5246 | 4706 | -540 | 0.21 |
| May | 5589 | 5299 | -290 | 0.39 |
| Jun | 6249 | 5390 | -859 | 0.40 |
| Jul | 6324 | 6186 | -138 | 0.20 |
| Aug | 6185 | 6228 | 43 | 0.19 |
| Sep | 5690 | 5587 | -103 | 0.39 |
| Oct | 5544 | 5331 | -213 | 0.39 |
| Nov | 5282 | 5043 | -239 | 0.33 |
| Dec | 5115 | 4657 | -458 | 0.19 |

**Table 8a. DID for Change in Difference in Crime Rate for Chicago and Milwaukee 2012-2013 [Motor vehicle theft]**

| Month | Difference Between Chicago and Milwaukee 2012 | Difference Between Chicago and Milwaukee 2013 | Change in Difference in Crime Rates 2012-2013 | P-Value |
|---|---|---|---|---|
| Jan | 1133 | 1145 | 12 | 0.13 |
| Feb | 947 | 1010 | 63 | 0.38 |
| Mar | 1065 | 783 | -282 | 0.11 |
| Apr | 939 | 648 | -291 | 0.01 |
| May | 1059 | 682 | -377 | 0.02 |
| Jun | 1089 | 717 | -372 | 0.04 |
| Jul | 881 | 673 | -208 | 0.02 |
| Aug | 773 | 613 | -160 | 0.00 |
| Sep | 798 | 500 | -298 | 0.00 |
| Oct | 913 | 351 | -562 | 0.00 |
| Nov | 1069 | 394 | -675 | 0.00 |
| Dec | 975 | 602 | -373 | 0.00 |

**Table 8b. DID Graph for Change in Difference in Crime Rate for Chicago and Milwaukee 2012-2013 [Motor vehicle theft]**

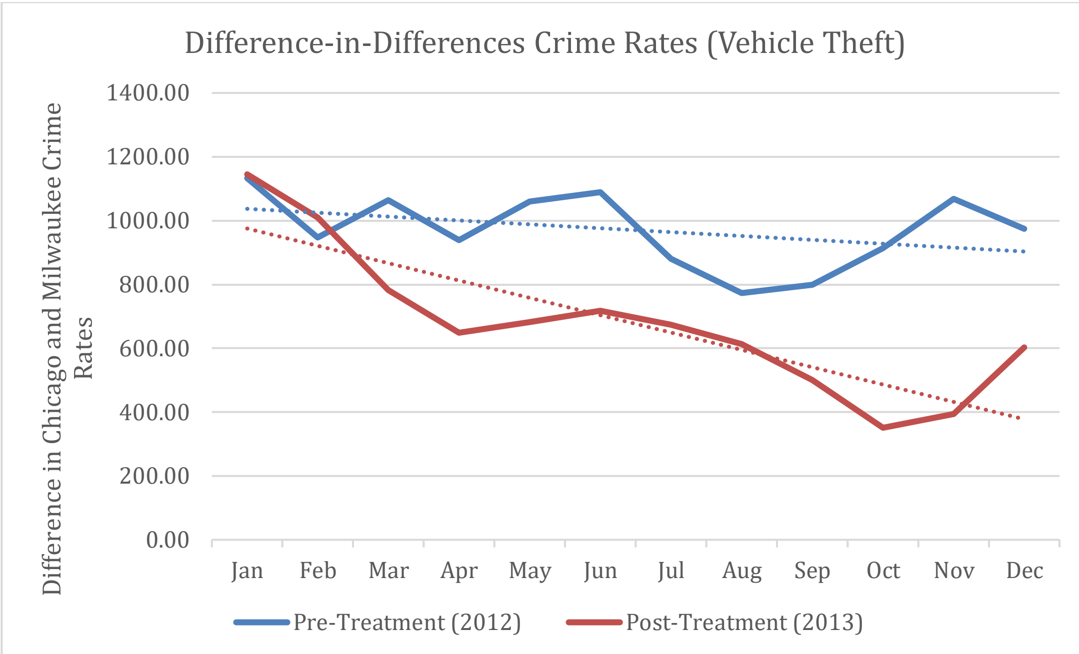


**Table 9. Differences in Chicago Crime Rate 2013-2014 [Arson]**

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| ARSON | 2013 | Average actual crime rate | 36.684 | Standard Deviation | 7.691 | | |
| | | Average predicted crime rate (2013): | 30.333 | n | 12 | p-value | 0.007 |
| | 2014 | Average actual crime rate | 31.595 | Standard Deviation: | 9.858 | | |
| | | Average predicted crime rate | 33.083 | n | 12 | p-value | 0.348 |

**Table 10. Differences in Chicago Crime Rate 2013-2014 [Assault]**

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| ASSAULT | 2013 | Average actual crime rate | 1569.329 | Standard Deviation | 223.225 | | |
| | | Average predicted crime rate (2013): | 1497.667 | n | 12 | p-value | 0.215 |
| | 2014 | Average actual crime rate | 1486.382 | Standard Deviation: | 241.055 | | |
| | | Average predicted crime rate | 1408.583 | n | 12 | p-value | 0.214 |

**Table 11. Differences in Chicago Crime Rate 2013-2014 [Criminal Damage]**

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| CRIMINAL DAMAGE | 2013 | Average actual crime rate | 2476.049 | Standard Deviation | 334.734 | | |
| | | Average predicted crime rate (2013): | 2571.083 | n | 12 | p-value | 0.246 |
| | 2014 | Average actual crime rate | 2103.44 | Standard Deviation: | 329.144 | | |
| | | Average predicted crime rate | 2316.5 | n | 12 | p-value | 0.032 |

**Table 12. Differences in Chicago Crime Rate 2013-2014 [Homicide]**

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| HOMICIDE | 2013 | Average actual crime rate | 38.954 | Standard Deviation | 12.3 | | |
| | | Average predicted crime rate (2013): | 35.75 | n | 12 | p-value | 0.266 |
| | 2014 | Average actual crime rate | 39.303 | Standard Deviation: | 9.249 | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | Average predicted crime rate | 35.5 | n | 12 | p-value | 0.145 |

**Table 13. Differences in Chicago Crime Rate 2013-2014 [Robbery]**

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| ROBBERY | 2013 | Average actual crime rate | 1045.844 | Standard Deviation | 145.542 | | |
| | | Average predicted crime rate (2013): | 985 | n | 12 | p-value | 0.14 |
| | 2014 | Average actual crime rate | 977.602 | Standard Deviation: | 127.251 | | |
| | | Average predicted crime rate | 816.583 | n | 12 | p-value | 0.00 |

**Table 13. Differences in Chicago Crime Rate 2013-2014 [Sex Offense]**

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| SEX OFFENSE | 2013 | Average actual crime rate | 72.869 | Standard Deviation | 18.001 | | |
| | | Average predicted crime rate (2013): | 87.25 | n | 12 | p-value | 0.01 |
| | 2014 | Average actual crime rate | 62.827 | Standard Deviation: | 19.181 | | |
| | | Average predicted crime rate | 83.417 | n | 12 | p-value | 0.00 |

**Table 14. Differences in Chicago Crime Rate 2013-2014 [Theft]**

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| THEFT | 2013 | Average actual crime rate | 6226.523 | Standard Deviation | 774.685 | | |
| | | Average predicted crime rate (2013): | 5960.917 | n | 12 | p-value | 0.20 |
| | 2014 | Average actual crime rate | 6162.54 | Standard Deviation: | 710.281 | | |
| | | Average predicted crime rate | 5130.417 | n | 12 | p-value | 0 |

**Table 15. Differences in Chicago Crime Rate 2013-2014 [Motor vehicle theft]**

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| MOTOR VEHICLE THEFT | 2013 | Average actual crime rate | 1450.625 | Standard Deviation | 163.016 | | |
| | | Average predicted crime rate (2013): | 1048.5 | n | 12 | p-value | 0.00 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 2014 | Average actual crime rate | 1438.964 | Standard Deviation: | 87.086 | | |
| | | Average predicted crime rate | 825.917 | n | 12 | p-value | 0.00 |

**Table 16. Differences in Changes in Chicago Crime Rate 2013-2014 [Arson]**

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| ARSON | 2013 | Average change in actual (2013): | 0.067 | Standard Deviation: | 0.298 | | | |
| | | Average change in predicted (2013): | 0.016 | n | 12 | z-score for 2013: | 0.593 | 0.335 |
| | 2014 | Average change in actual (2013): | 0.036 | Standard Deviation | 0.275 | | | |
| | | Average change in predicted (2014): | 0.03 | n | 12 | z-score for 2014: | 0.076 | 0.398 |

**Table 17. Differences in Changes in Chicago Crime Rate 2013-2014 [Assault]**

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| ASSAULT | 2013 | Average change in actual (2013): | 0.001 | Standard Deviation: | 0.122 | | | |
| | | Average change in predicted (2013): | -0.011 | n | 12 | z-score for 2013: | 0.341 | 0.376 |
| | 2014 | Average change in actual (2013): | 0.007 | Standard Deviation | 0.144 | | | |
| | | Average change in predicted (2014): | 0.015 | n | 12 | z-score for 2014: | -0.192 | 0.392 |

**Table 18. Differences in Changes in Chicago Crime Rate 2013-2014 [Criminal Damage]**

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| CRIMINAL DAMAGE | 2013 | Average change in actual (2013): | 0.022 | Standard Deviation: | 0.151 | | | |
| | | Average change in predicted (2013): | -0.007 | n | 12 | z-score for 2013: | 0.665 | 0.32 |
| | 2014 | Average change in actual (2013): | 0.003 | Standard Deviation | 0.139 | | | |
| | | Average change in predicted (2014): | 0.016 | n | 12 | z-score for 2014: | -0.324 | 0.379 |

**Table 19. Differences in Changes in Chicago Crime Rate 2013-2014 [Homicide]**

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| HOMICIDE | 2013 | Average change in actual (2013): | 0.041 | Standard Deviation: | 0.407 | | | |
| | | Average change in predicted (2013): | 0.074 | n | 12 | z-score for 2013: | -0.281 | 0.383 |
| | 2014 | Average change in actual (2013): | 0.012 | Standard Deviation | 0.257 | | | |
| | | Average change in predicted (2014): | 0.033 | n | 12 | z-score for 2014: | -0.283 | 0.383 |

**Table 20. Differences in Changes in Chicago Crime Rate 2013-2014 [Robbery]**

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| ROBBERY | 2013 | Average change in actual (2013): | 0.022 | Standard Deviation: | 0.157 | | | |
| | | Average change in predicted (2013): | 0.011 | n | 12 | z-score for 2013: | 0.243 | 0.387 |
| | 2014 | Average change in actual (2013): | 0.01 | Standard Deviation | 0.17 | | | |
| | | Average change in predicted (2014): | 0.005 | n | 12 | z-score for 2014: | 0.102 | 0.397 |

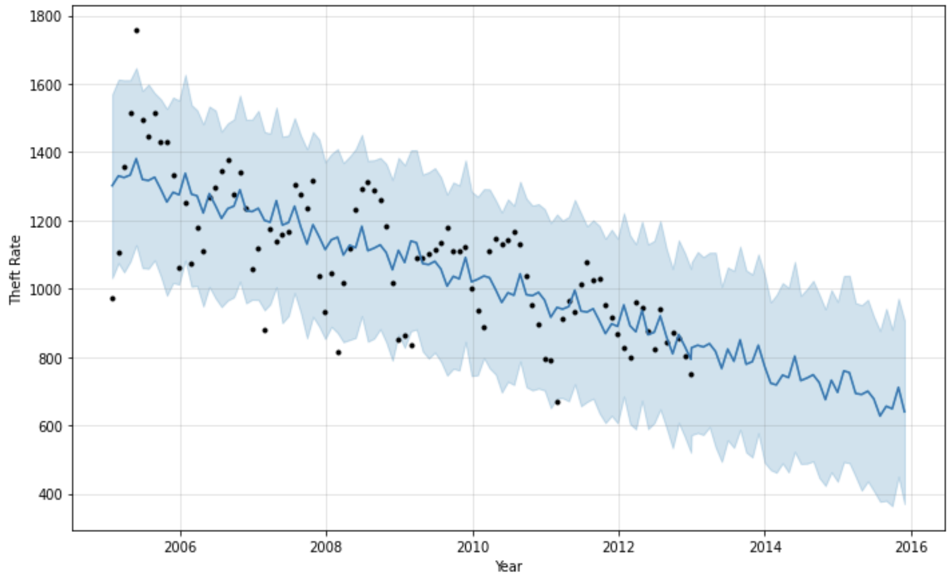
**Table 20. Differences in Changes in Chicago Crime Rate 2013-2014 [Theft]**

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| THEFT | 2013 | Average change in actual (2013): | 0.008 | Standard Deviation: | 0.106 | | | |
| | | Average change in predicted (2013): | 0.003 | n | 12 | z-score for 2013: | 0.163 | 0.394 |
| | 2014 | Average change in actual (2013): | 0.006 | Standard Deviation | 0.108 | | | |
| | | Average change in predicted (2014): | -0.004 | n | 12 | z-score for 2014: | 0.321 | 0.379 |

**Table 21. Differences in Changes in Chicago Crime Rate 2013-2014 [Motor vehicle theft]**

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| MOTOR VEHICLE THEFT | 2013 | Average change in actual (2013): | 0.003 | Standard Deviation: | 0.091 | | | |
| | | Average change in predicted (2013): | -0.03 | n | 12 | z-score for 2013: | 1.256 | 0.181 |
| | 2014 | Average change in actual (2013): | 0.005 | Standard Deviation | 0.168 | | | |
| | | Average change in predicted (2014): | -0.011 | n | 12 | z-score for 2014: | 0.33 | 0.378 |

**Table 22. Graphed Predictions of Milwaukee Annual Crime Rates Methods Test**



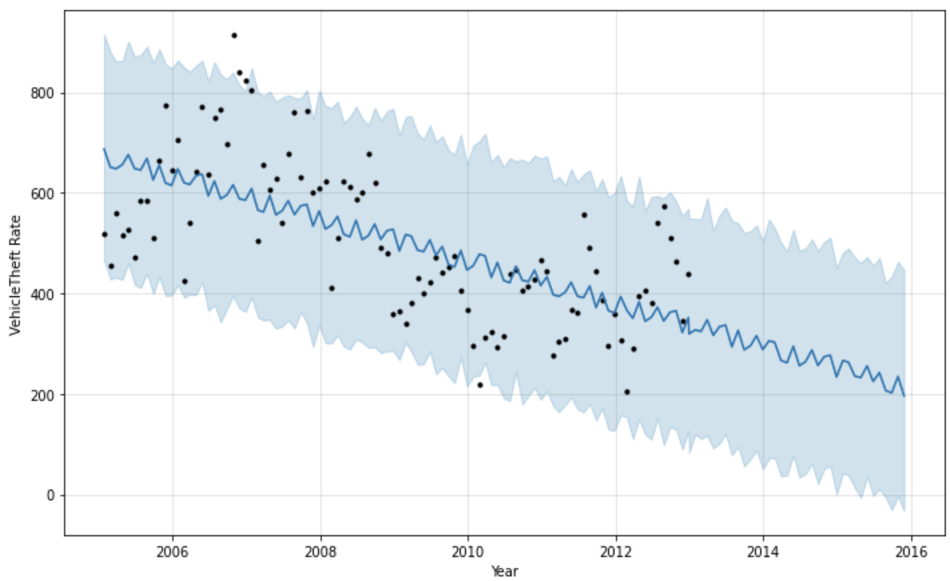



**Table 23. Graphed Predictive Seasonality of Motor vehicle thefts in Chicago**

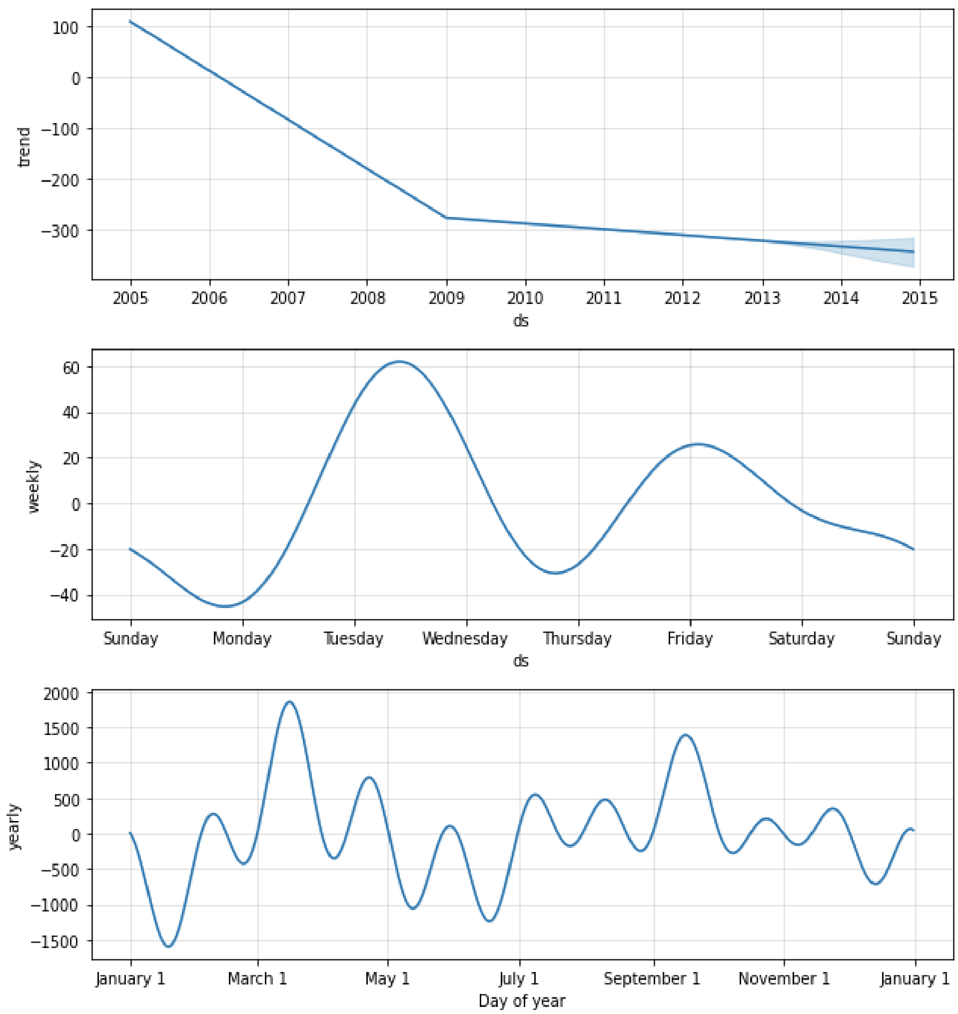


**Table 24. Graphed Predictions of Chicago Crime Rates for 2013-2015 [Arson]**

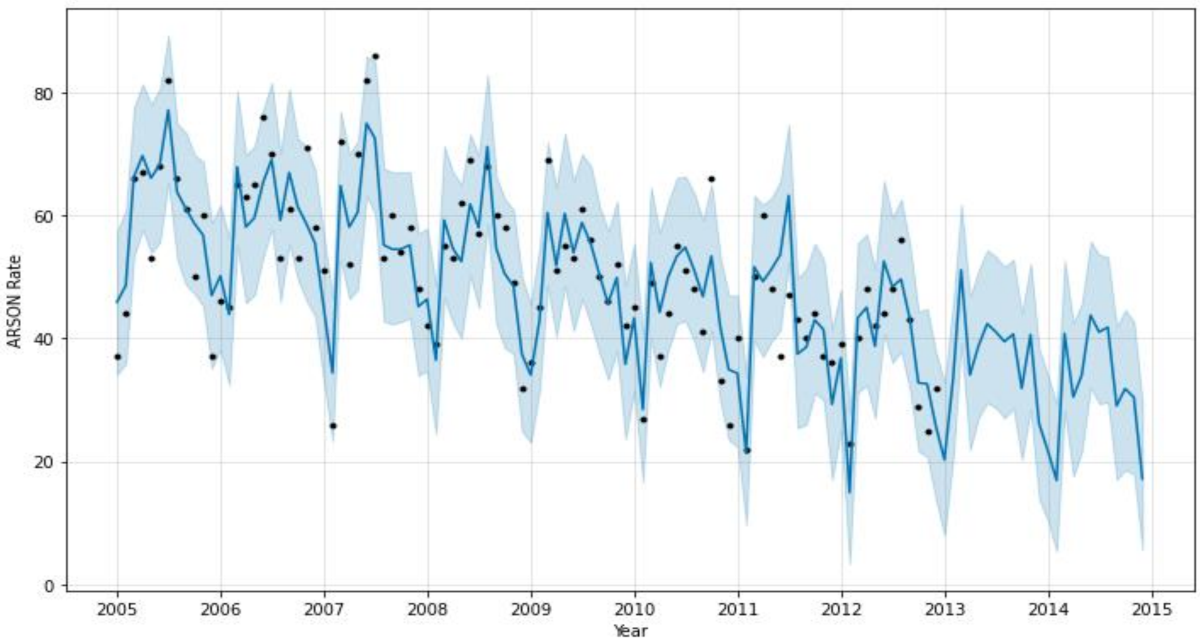



**Table 25. Graphed Predictions of Chicago Crime Rates for 2013-2015 [Assault]**

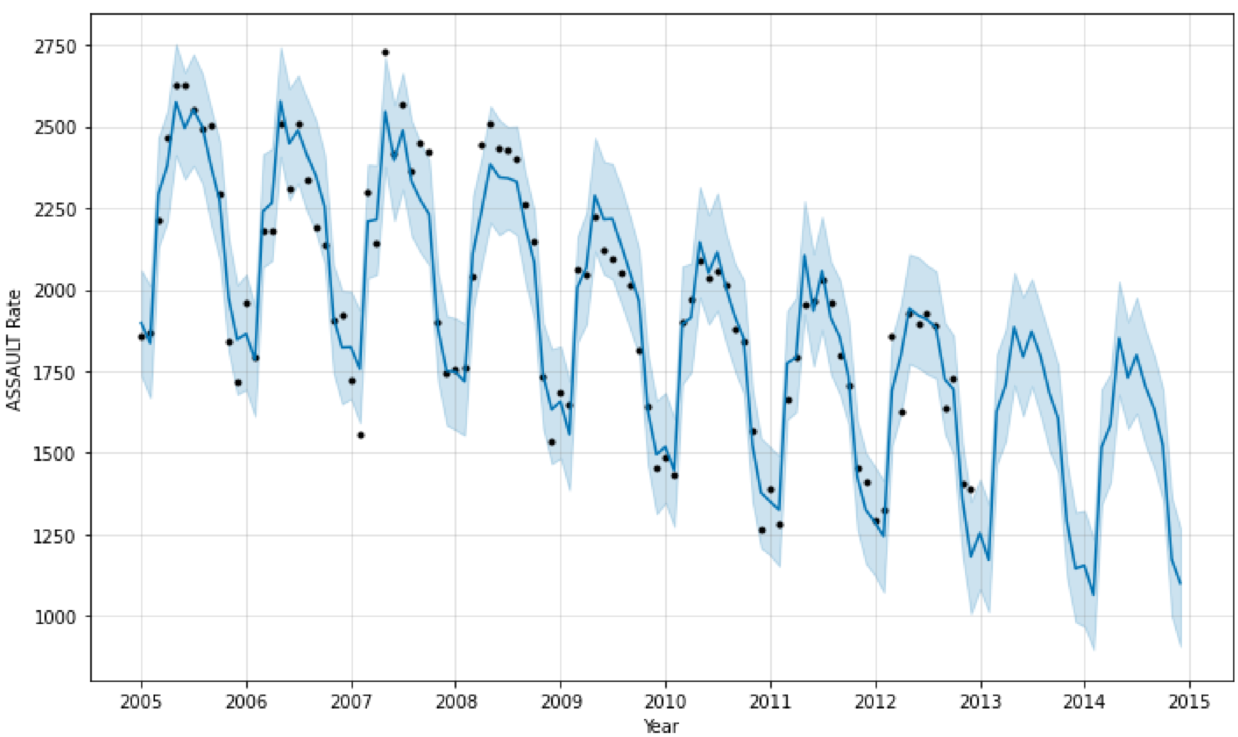


**Table 26. Graphed Predictions of Chicago Crime Rates for 2013-2015 [Criminal Damages]**

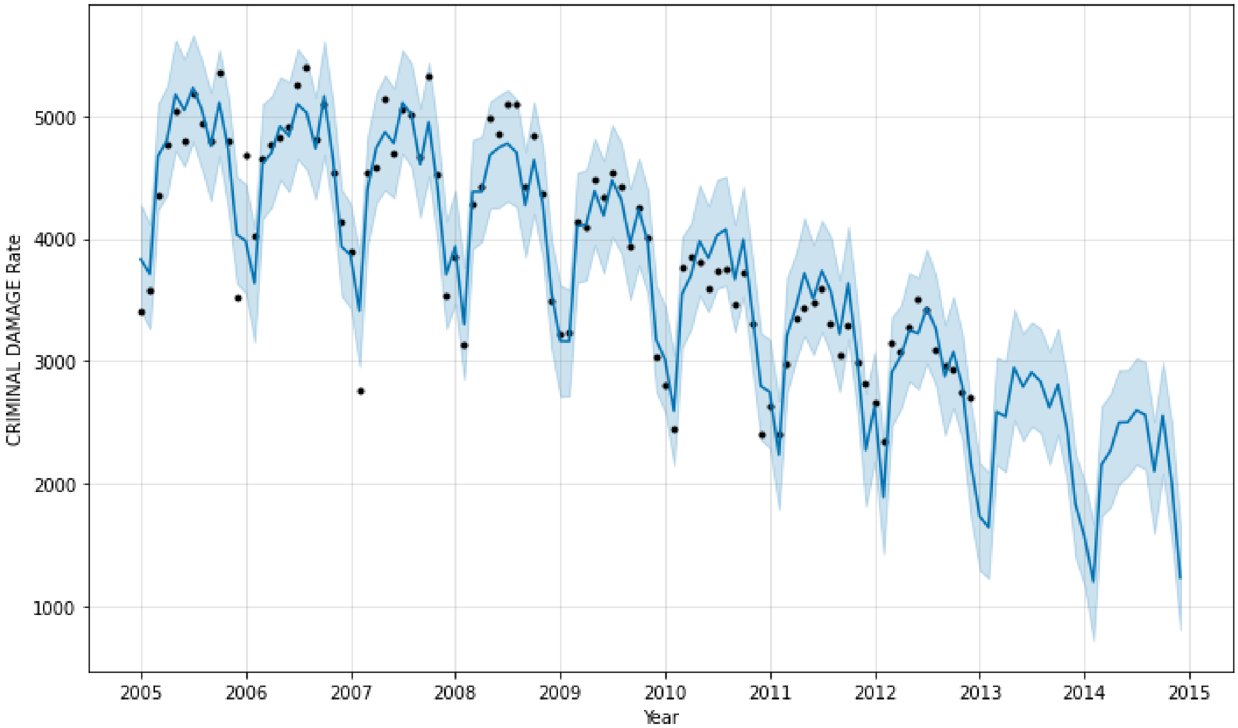



**Table 27. Graphed Predictions of Chicago Crime Rates for 2013-2015 [Homicide]**

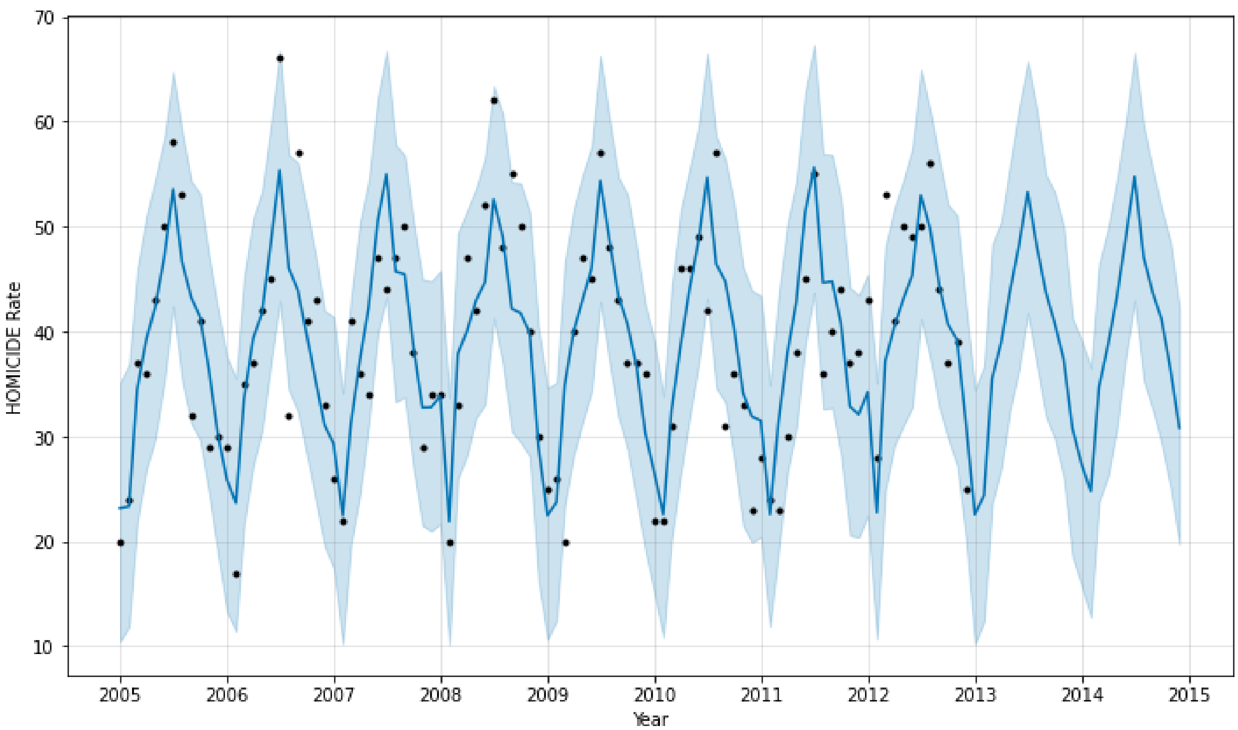


**Table 28. Graphed Predictions of Chicago Crime Rates for 2013-2015 [Robbery]**

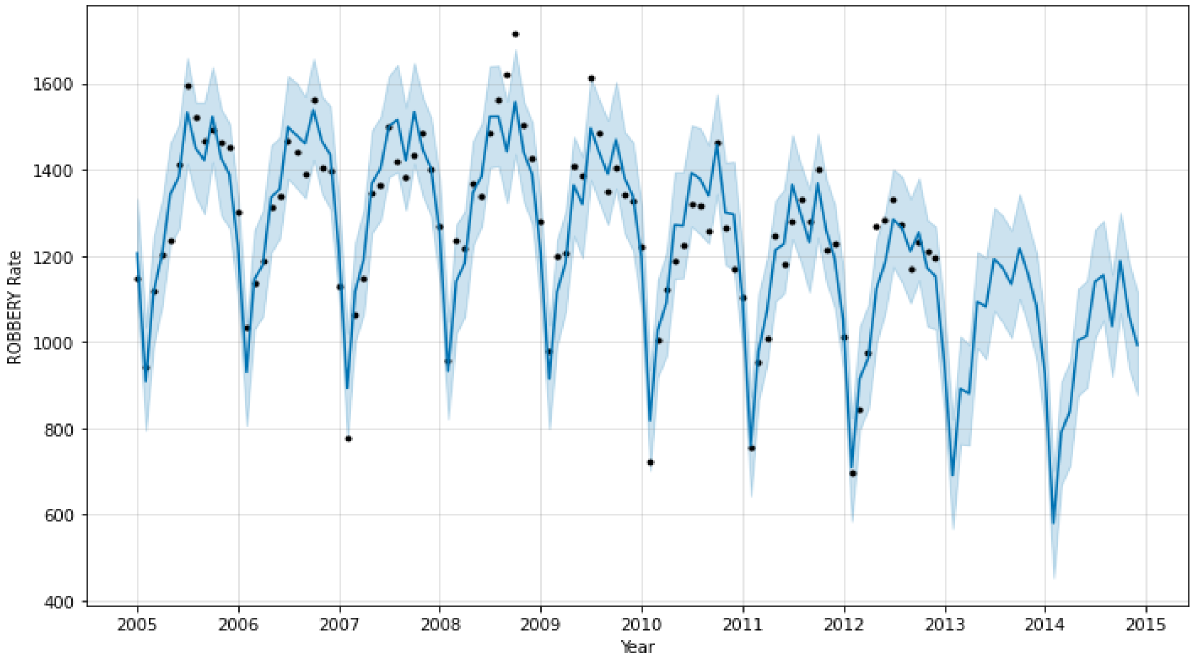



**Table 29. Graphed Predictions of Chicago Crime Rates for 2013-2015 [Sex Offense]**