# Fighting Crime with Taxes

How Opportunity Zones Impacted Crime in Chicago

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## ABSTRACT

While there are many approaches to combat crime in Chicago, most strategies focus on policing, whether that is through an increased police presence or community-centered policing tactics. But there are other viable, unconventional approaches to reduce crime, such as educational reforms, mental health services, and economic development programs. In this paper, I will focus on one of these other, more untraditional approaches – economic development – by exploring how the Opportunity Zone program, an economic, placed-based policy implemented through the federal tax code, impacted crime specifically in Chicago. The Opportunity Zone policy provides tax benefits to investors that fund projects in Qualified Opportunity Zones, which are census tracts identified as areas in economic distress by the IRS and local government. The intention of this tax program is to incentivize private economic stimulus in disinvested communities. It was not designed as a targeted solution to reduce crime. Nonetheless, because the derivations of criminal activity are often rooted in the lack of economic opportunity, I seek to examine in this paper how this economic development program unintentionally impacts crime rates in Chicago. Through a difference-in-differences research design, I conduct a linear regression analysis that drew from American Community Survey, IRS, and City of Chicago data. My analysis finds that the implementation of the Opportunity Zone policy in Chicago led to a decrease in total and violent crime rates in Qualified Opportunity Zones, indicating that the implementation of the policy unintentional reduced crime rates in these Zones. These results suggest economic development programs implemented through the tax code, like Opportunity Zones, could be a viable solution to fight crime. Thus, I recommend that state and federal governments further explore this potential and evaluate the costs and benefits of programs like Opportunity Zones. Similar policies could prove to have far-reaching, positive effects on disinvested communities, and this analysis is just a start in exploring this possibility.

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## INTRODUCTION

While cities and towns across the country have struggled with the issue of crime, one city is in conversation a lot when it comes to crime – Chicago. Just like many other American cities, the crime problem in Chicago has led to significant academic research, political pressure, and calls for change from the people. These calls to action have motivated the city to invest millions of dollars to combat rising crime rates. In 2022, the city invested more than $11 million to reduce violence and create new systems of support for victims (City of Chicago 2020, 4). From this funding, a plethora of policy ideas and social action arose, but these policy solutions often focus on either policing, community engagement, or education. It is rare that Chicago crime reduction plans address the economic derivations of crime. And if they do address the economic forces driving crime, it is usually in passing and just stating the issue without proposing a plan of substance.

Because of this lack of economic focus within crime discussions, I wanted to explore how economic development programs could reduce crime by treating the economic desperation in communities that often fuels criminal activity. Fortunately, for my project, I discovered the federal tax program of Opportunity Zones or Enterprise Zones, which has become a popularized place-based or community centered economic policy that encourages the revitalization of distressed areas through tax-incentivized, targeted investments. This led me to question how an economic development program like Opportunity Zones could impact crime specifically in Chicago. To answer this question, the following analysis will look specifically at Chicago and how the 133 designated Opportunity Zones in the city have influenced crime rates (City of Chicago 2022).

Based on my own initial research, I expected the crime rate in Chicago to decrease in response to the enactment of the Opportunity Zones policy in Chicago, because of the increase in economic opportunity. My hypothesis is based on extensive research of the criminal justice system in my academic studies and as an intern for the Cook County State's Attorney's Office. Through these experiences, I learned about the derivations of crime in Chicago, the possible solutions to the crime problem, the importance of investing in disadvantaged communities, and the reactions to Opportunity Zones. To test the validity of my hypothesis, I conducted a difference-in-differences statistical design because it fit within the research constraints of having limited time and resources to generate my own experiment and because it provided an opportunity to draw out a causal relationship. The data used for this model comes from the American Community Survey, Internal Revenue Service, and the City of Chicago Data Portal, with data aggregated from 2016 to 2020 ("American Community Survey"; "Crimes – 2001 to Present – Map" 2022; IRS 2018). The results of the model show that census tracts designated as Opportunity Zones saw a greater decrease in their estimated total and violent crime rates. This indicates that the Opportunity Zone policy, a place-based economic development program implemented through the tax code, had a positive impact on crime in Chicago, suggesting the policy unintentionally led to a reduction in crime. Thus, place-based, economic development policies, like Opportunity Zones, are worthwhile programs to consider when fighting crime.

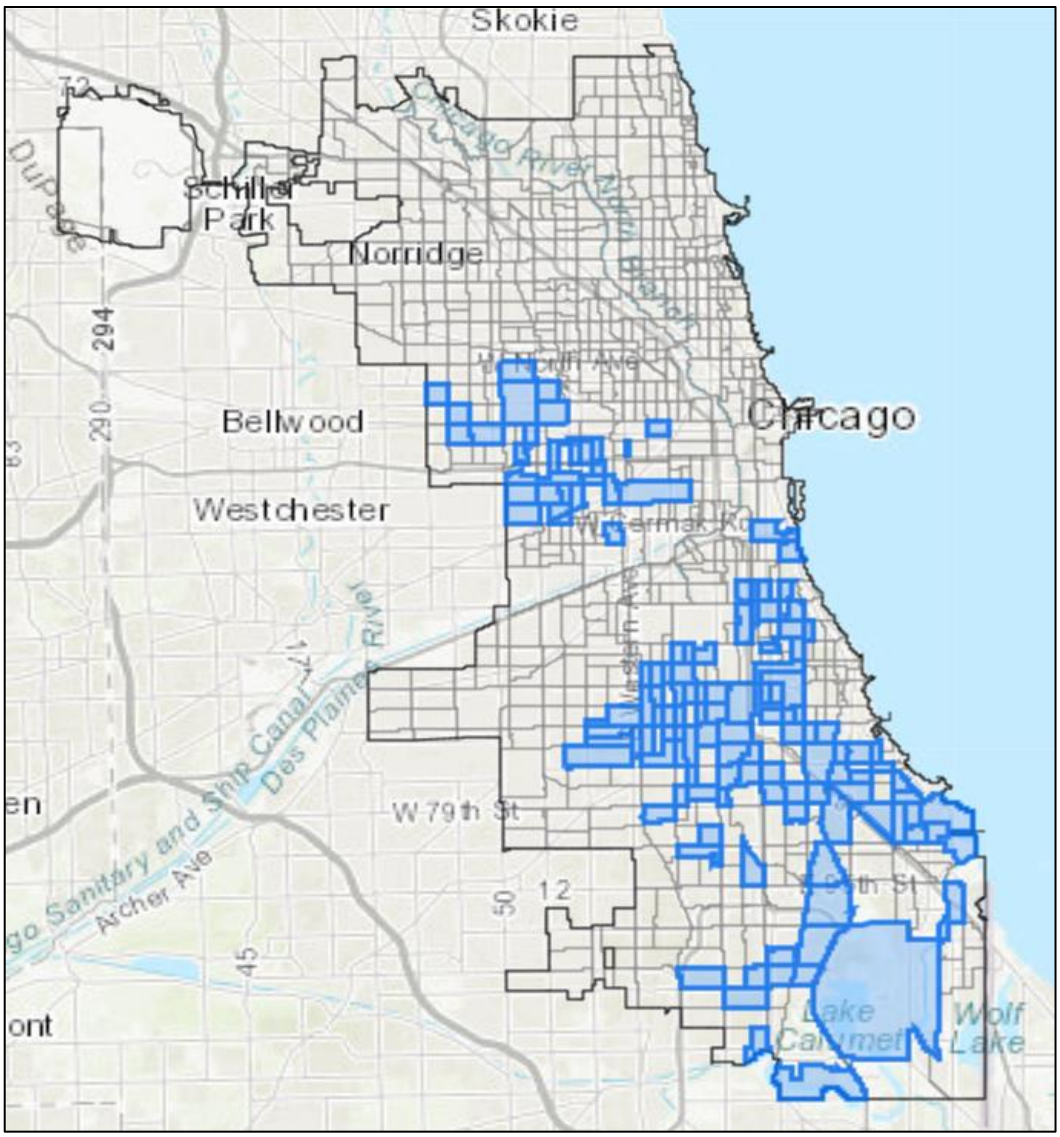
## BACKGROUND

Federally, Opportunity Zones were enacted under the 2017 Tax Cuts and Jobs Act to revitalize disadvantaged communities. Different versions of Opportunity Zones were implemented at the state-level before federal enactment. For example, California implemented an enterprise zone policy in 1984 that aimed to incentivize job creation in Targeted Employment

Areas (TEAs) (Neumark and Simpson 2015, 1201; KBKG 2022). While Opportunity Zones have gone through many iterations within different municipalities, the key components are the same – implement a place-based policy that incentivizes reinvestment in distressed areas.

The Zones are census tracts that have been approved by the Department of Treasury as areas with low-income communities and in need of redevelopment (IRS 2022). For tax purposes, these designated Zones are labeled as "Qualified Opportunity Zones". The federal program works by offering investors the chance to defer temporarily their capital gains taxes if they invest

**Figure 1:** Map of the City of Chicago divided by census tracts. The blue, highlighted census tracts are designated Opportunity Zones (City of Chicago 2022).



their assets into a Qualified Opportunity Fund (QOF). These QOFs are an investment vehicle that establishes a partnership for the purpose of investing in property or other forms of capital in Qualified Opportunity Zones (IRS 2022). This tax structure allows companies, investors, entrepreneurs, and business owners to gain a tax break on their capital gains taxes if they finance a QOF, saving them money while also reinvesting in these disadvantaged communities. However, the size of the tax break depends on the duration of time these assets are in the QOF (IRS 2022).

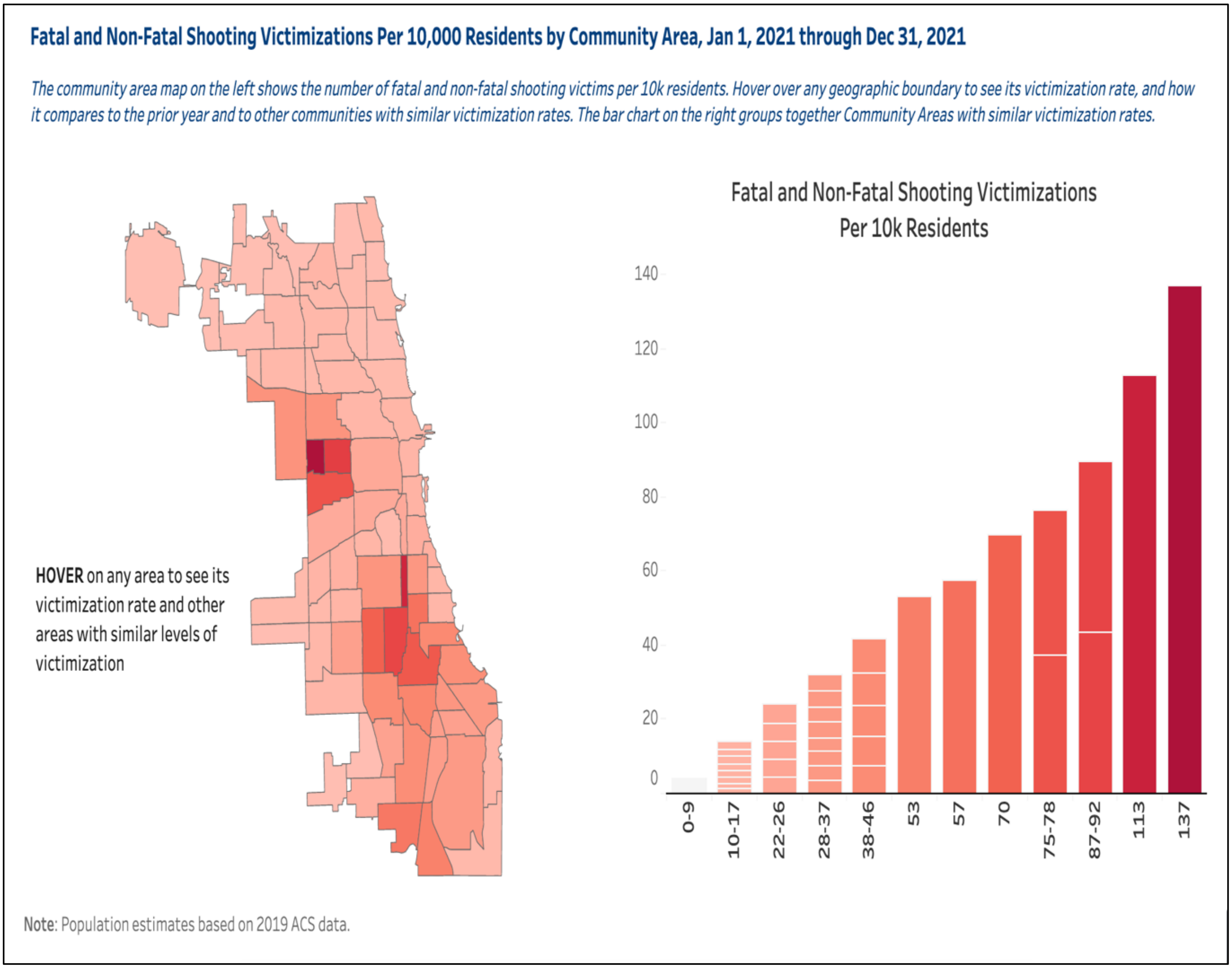
## LITERATURE REVIEW

### Crime in Chicago

The current literature on crime in Chicago reveals that crime is not only a major problem, but highly concentrated and the proposals thus far have been inadequate at reducing criminal activity. Such failures call into question why this is the case and how economic investments in these higher crime areas could decrease crime rates by funding other pathways than the police.

Crime statistics from the Chicago Police Department, which are collected and aggregated through COMPSTAT, show that in 2021, 804 murders, 2,067 criminal sexual assaults, 7,911 robberies, and 10,590 motor vehicle thefts occurred in the city (Chicago Police Department). This criminal activity is highly concentrated in certain disadvantaged communities, as indicated in Figure 2. These areas not only have higher rates of crime but also higher unemployment rates, lower incomes per capita, and higher rates of infant mortality. The infant mortality rate is included here because it is a key metric describing the health of society, and good health is highly correlated with economic prosperity (Braveman P., 2018; Centers for Disease Control and Prevention). For example, a study published in the University of Chicago Law Review found that in Austin and Englewood, two neighborhoods in Chicago with high rates of crime, the unemployment rate was around 21% and the infant mortality rate was around 13 deaths per 1,000 live births in both neighborhoods. But, in Lincoln Park, a more affluent neighborhood with less crime overall, the unemployment rate was around 4.5% and the infant mortality rate was around 2.4 deaths (Huq and Rappaport 2022, 312). Such disparities amongst these neighborhoods indicate that living in a poor and jobless neighborhood might contribute to the violence prevalent in these areas (Sharkey and Marsteller 2022, 349).

**Figure 2:** Map generated using the City of Chicago's Violence Reduction Dashboard ("Violence Reduction Dashboard").



Nonetheless, any potential solution to crime in Chicago has reverted to increased policing power through additional funding and support from city government, which has been inadequate and only widened the racial inequalities invasive in the criminal justice system. By looking at city officials' rhetoric on crime and studying crime data, the Harvard Law Review Forum found that through increased rhetoric about illegal guns and the enforcement of gun possession laws, the Chicago Police Chief and mayor legitimized an increase in policing when the social climate had called for reform and rectification for how increased policing disproportionately impacts communities of color (Huq, Vargas, and Loftus 2022, 474). Unfortunately, this is on par with how crime in Chicago has traditionally been dealt with. A study of the city's response to homicide crime waves in 1920-1925, 1966-1970, 1987-1992, and in 2016 exposes the CPD's diversion of responsibility from the mayor and police, by advancing anti-Black sentiments and by monopolizing crime data to legitimize notions that the only solution is to maintain traditional crime fighting methods – funding the police (Vargas et al. 2022, 406). Thus, the response and solutions to crime in Chicago have defaulted to historical practices of funding the police that are inadequate and rooted in racism.

***Place-Based Policies as a Potential Solution***

Recent literature has offered placed-based policies, a policy strategy that is intended for a specific area or community, as a potential solution to these structurally and culturally challenging problems in trying to fight crime. Place-based policies are a viable solution and show that there is a relationship between violence and place, such as when gun violence is concentrated in segments of disinvested communities, thus indicating that investing in these disadvantaged areas could be a more effective strategy in fighting crime (Love 2021, 2). This connection between place and crime, established by Hanna Love at the Brookings Institution, provides a framework for investment along four key dimensions – a place's economic health, built environment, social environment, and civic infrastructure – which could reduce violence and support communities in their ability to thrive (Love 2021, 2). Love utilizes existing studies to support her argument that the criminal legal system is the status quo for addressing crime, when our society should be making place-based investments to mitigate the causes of violence (Love 2021, 4). This offers a new direction for crime reduction strategies instead of the traditional crime fighting policies that increase resources for policing.

## Opportunity Zones

The federal Opportunity Zones program serves as a place-based policy because it seeks to spur economic reinvest in certain census tracts that are designated Qualifying Opportunity Zones, which is the unit of classification used by the IRS. These Qualified Opportunity Zones are the physical areas the IRS incentivizes private investment by providing tax benefits to those who invest funds or assets in these communities (IRS 2022). In this section, the literature on Opportunity Zones, including both the economics and case studies available, will be explored to deduce the economic development program's success as a place-based policy and whether it could have any unintentional effect on social issues like crime.

### *Economic Theory Regarding Opportunity Zones*

An article published in the Handbook of Regional and Urban Economics discusses the economic theory behind place-based economic development programs and speaks generally about Opportunity Zones. The research carries out an extensive literature review on the imperfections in labor economies, such as the spatial mismatch hypothesis and externalities from network effects, that provide a rationale for place-based policies. The spatial mismatch hypothesis argues that the disadvantages minorities or low-skilled workers face in urban areas are often spurred by rapid decline in employment opportunities, housing discrimination, and other constraints that restrict the mobility of people to migrate to locations with better economic opportunities (Neumark and Simpson 2015, 1199). Therefore, because of spatial mismatch, it might be worthwhile to invest in place-based economic development programs to aid people physically stuck in these jobless areas. Positive externalities from network effects provide another argument for place-based economic policies because they naturally benefit third parties. These positive externalities occur when residents start their own businesses or become employed, creating a spillover effect resulting in other residents being able to find more work (Neumark and Simpson 2015, 1200). The Opportunity Zone policy exploits this positive externality by facilitating agglomeration, which occurs by monopolizing positive externalities to create long-term gains in a targeted area. This agglomeration can spur increased job opportunities, in-migration, and the attraction of more industry and development (Neumark and Simpson 2015, 1206).

Nonetheless, a Place-Based Policies report outlines some limitations when it comes to location centric policies that try to utilize these market failures, like Opportunity Zones. One of those limitations is whether positive externalities benefit disadvantaged folks via the place-based policy. It is possible that the jobs created by the economic development program could go to nonpoor residents, which could spur gentrification by solely benefiting advantaged communities. To solve this, the article suggests creating institutional arrangements such as "Community Benefit Agreements", which mandate that new, invested jobs go to the local population, ensuring the gains go to their intended recipients (Neumark and Simpson 2015, 1213). Another limitation discusses the potential of negative spillover effects when it comes to place-based policies. While studies found that Opportunity Zones led to job growth, these results might be considered differently if the jobs created were the result of new jobs or employers moving from another area to take advantage of the enterprise zone credits (Neumark and Simpson 2015, 1225). While this migration could benefit the new community, it could also leave the original community worse off, essentially counteracting the positive effect. Therefore, when debating place-based policies, it is important to consider the direction of the agglomeration effects and whether there will be positive or negative spillover. The direction of these effects could greatly impact the validity of investing in place-based policies, like Opportunity Zones.

### ***Case Studies of Opportunity Zones***

The Opportunity Zones created under the 2017 Tax Cuts and Jobs Act incentivized investments in property, businesses, and joint ventures more so than ever before (Williams 2022, 483-484). This place-based program focuses on the economic health dimension of the place-based intervention strategy Love provides and attempts to exploit the market failures outlined above. While the ultimate goal of the program is to encourage competitive business practices in designated low-income areas based on census tract data, the actual implementation and effects of the policy have been somewhat controversial (Williams 2022, 488-489).

Opportunity Zones are an effective way to begin development in disadvantaged communities, but the implementation and oversight of Opportunity Zones is crucial in the program having a noticeable effect in these communities. A case study conducted through 76 qualitative interviews examines the strengths and weaknesses of Opportunity Zones in West Baltimore and Baltimore City (Snidal and Newman 2022, 27). The study found that while Opportunity Zones are stimulating a new set of investors, spurring development conversations, and encouraging local government involvement, they ultimately are failing to engage the community on revitalization and not changing the economic development prospects in distressed neighborhoods (Snidal and Newman 2022, 33-38). This failure to improve these disadvantaged communities comes from the lack of oversight and incentives for investors within the program (Snidal and Newman 2022, 45-46). This case study is an example of the gentrification and negative spillover effects warned about in the economics literature.

Another case study regarding Ogden Commons in North Lawndale, Chicago revealed similar problems to the ones faced in the West Baltimore case, advancing the claim that the Opportunity Zone tax incentive is funding projects in already gentrifying communities. These unintentional effects have allowed investors to drive billions of investment profits into luxury apartments, hotels, student housing, and storage facilities, which are not aiding the mission of helping low-income communities (Kaye 2021, 1103). Nonetheless, both case studies support reform within the Opportunity Zone program to increase community engagement and policy oversight (Kaye 2021, 1104-1106; Snidal and Newman 2022, 36-41). These examples demonstrate that while there are problems with the place-based economic development program, there is still potential for the program if it is reformed.

While the theory and case studies reveal the limitations and improvements to be made in the Opportunity Zone program, they do not begin to untangle the effects this economic development program has on crime in the area. This exposes a gap in the literature, and by narrowing my study to the effects of Opportunity Zones in Chicago specifically, I will be able to draw out how this place-based, economic development program impacts crime in my own city.

## METHODOLOGY

I conducted a quantitative analysis that utilized a difference-in-differences model to determine whether Opportunity Zones had any effect on crime in Chicago. The first step in my project was to aggregate the data. I pulled data from the City of Chicago Data Portal, American

Community Survey, and IRS. The units of data in this analysis are census tracts, and I looked at data from a timespan of 2016 to 2020 because the Qualified Opportunity Zones in Chicago were approved by the Department of Treasury on July 9th, 2018, allowing trends to be examined over a time-period of four years – two years before and after the approval of Chicago's Opportunity Zones (IRS 2018, 9). The City of Chicago Data Portal aggregates all the city's datasets and has a page dedicated to public safety, which is where I found crime data on incident reports from the Chicago Police Department from 2001 to present day ("Crimes – 2001 to Present – Map"). The American Community Survey is conducted through the U.S. Census Bureau and provides yearly estimates, which is where the data on race, educational attainment, socioeconomic factors, and population were collected. This is a widespread survey that collects data points on demographic information through mailed questionnaires, telephone interviews, and visits from Census Bureau representatives (U.S. Bureau of Labor Statistics 2022). While there are multiple ways to collect the data for Qualified Opportunity Zones, the official press release from the IRS provided the most accurate depiction of the data. The IRS announced a press release on July 9th, 2018 that listed all of the approved Qualified Opportunity Zones in Chicago, marking their official status as preferential areas for investment (IRS 2018, 59-63). This provided a verified and credible source of when the Opportunity Zone policy was officially in effect in Chicago.

After gathering all the data, I cleaned and generated a final dataset to run my regression analysis using R v.3.3. The first step in building my analytic dataset was cleaning the crime data, so that every reported crime was classified into the correct census tract. Since the data from the City of Chicago Crime Portal includes the location of every crime incident by longitude and latitude, I used the *sf* and *dplyr* packages in R and a shapefile with the coordinates of each census tract in Cook County to match each crime incident using its longitude and latitude with the corresponding census tract. The second step was to examine the crime data and determine which crimes were violent and non-violent. To do this, I reviewed all the different types of crime in the dataset (theft, assault, battery, narcotics, etc.), and I classified the types of crime as either violent or non-violent (Appendix 1). In my classification, I used the FBI's definition for a violent crime, which is defined as a crime of force or threatened force against a person ("FBI: UCR"). This crime dataset now had variables for violent and non-violent crime, which were later used to calculate total, violent, and non-violent crime rates. The third step was to organize the ACS data, which detailed socioeconomic information for each census tract in Chicago, and merge it with the IRS data, which listed the census tracts in Chicago that are designated Qualified Opportunity Zones. Through a left-joining process, I merged the ACS data with the IRS data, creating a dataset that listed every census tract in Chicago with its associated socioeconomic information and a binary variable indicating whether the census tract was a Qualified Opportunity Zone. The fourth step was to merge the cleaned crime dataset with this new ACS dataset, which was done through another left joining process. This generated a massive dataset that I then had to organize as my final analytic dataset. In the fifth step, I generated multiple variables within this combined dataset. The first set of variables were for crime rates. I calculated rates for total, violent, and non-violent crime by summing the crimes (by type) in each census tract in a given year and dividing by the population estimate from the ACS data. The second set of variables operationalized time for the downstream analyses. I created a binary time variable to capture pre vs. post implementation of the Opportunity Zone policy, with the years 2016 and 2017 coded as "0", and 2019 and 2020 coded as "1". The year 2018 was coded as "N/A" because this was the year the policy was initially enacted in Chicago, and I wanted to compare crime rates before and after official implementation. Finally, I arranged the dataset so that each census tract in Chicago had data for four years (2016-2020), listing the estimated socioeconomic information and crime rates for each year.

While this dataset is generated from credible sources, there are a few potential limitations to consider. The American Community Survey yields data based on 1-year estimates, which may be relatively unstable and prone to greater error and noise. To address this, I decided to use the corresponding 5-year estimates from the ACS, which provide more stable demographic representations, even though they may mask true changes over a short period. Furthermore, the crime data provided by the city is made up of incident reports, which means they do not capture convicted crimes. While it is unlikely that a police officer would generate an incident report without there actually being an incident, it is likely that some crime goes unreported, which raises questions about the comprehensiveness of the data. Despite these limitations, the data overall was publicly available, on a micro-level, and generated by reliable institutions, all providing strong justification for their use in my study.

With the final analytic dataset, I sought to test the hypothesis that the implementation of Opportunity Zones in Chicago caused a decrease in crime in those Zones, demonstrating that place-based economic development programs are a viable solution to reduce crime in urban areas. To test this hypothesis, I used a difference-in-differences research design because it is a quasi-experimental approach that allows for a causal relationship to be determined without having to conduct individual level randomization. In this model, the treatment or intent-to-treat is the designation of Qualified Opportunity Zones, which assumes the policy was successfully implemented once certain census tracts were approved by the Department of Treasury in 2018. The outcome variable is the crime rate within each census tract as calculated based on reported crime events collected by the City of Chicago. I used the richness of the ACS data to control for the potential confounding effects of race, educational attainment, income, and inequality on the relationship between the implementation of Opportunity Zones and crime rates by census tracts. In particular, the specific variable names of the covariates are mean percent non-white, mean percent Hispanic, mean young adult population less than High School, mean median household income, and mean Gini index (Table 1). While the covariates are not perfect, they are reasonable proxies for factors that might confound the results of the model.

**Table 1:** Variable Description

| ***Variable Type*** | ***Unit*** | ***Data Source*** |
|---|---|---|
| *Dependent* | Crime Rates | City of Chicago Crime Portal |
| *Independent* | Opportunity Zones | IRS |
| *Control* | Race | American Community Survey |
| *Control* | Inequality (Gini Index) | American Community Survey |
| *Control* | Educational Attainment | American Community Survey |
| *Control* | Income | American Community Survey |

But it is also important to note one covariate I could not control for in my model – the Coronavirus pandemic. The COVID-19 pandemic began in 2020, which is included in the timeframe of the data. It is hard to determine the impact COVID-19 had on crime and whether it could have influenced the model's results. However, I assumed that the impact of the COVID-19 pandemic on crime rates was similar across census tracts in and outside of Opportunity Zones and therefore its confounding influence on the analyses would be minimized. Moreover, I knew I would not be able to control for every potential confounder. I conducted a difference-in-differences study design specifically because of this concern, and I hoped that the model could remove as much bias and noise as possible, only leaving the causal effect desired. I decided not to carry out a simple regression or correlation analysis, because I wanted to be able to draw more credible causal inferences from my results. I knew this was risky considering the numerous effects that could influence my results, but through this analysis, I was able to derive a model to show the impact the Opportunity Zone policy has on crime in Chicago.

With my treatment, outcome, and control variables identified, I then carried out a linear regression analysis, where I created an interaction term to capture the impact Opportunity Zones had on three types of crime rates in Chicago – violent, non-violent, and total crime rates – over time. The equation below illustrates the linear regression model:

$$E[Y_{it}] = \beta_0 + \beta_1(OZ) + \beta_2(Time) + \beta_3(OZ * Time) *$$

- $\beta_0$ is the average crime rates for non-Opportunity Zones before the implementation of the policy.
- $\beta_1$ is the difference in average crime rates between non-Opportunity Zones and Opportunity Zones before the implementation of the policy.
- $\beta_2$ is the difference in average crime rates post-implementation minus pre-implementation for non-Opportunity Zones.
- $\beta_3$ is an interaction term for the difference between these differences over time, comparing the average crime rates in Opportunity Zones to non-Opportunity Zones.
- The model also controls for all the covariates mentioned in the previous paragraph, but these are not shown in the above equation.

While this regression analysis provides insight into how Opportunity Zones impacted crime rates in Chicago, there are statistical limitations prevalent. For example, the regression analysis does not include randomization which would provide the most robust approach for addressing possible confounding. Instead, covariates are included in the model to statistically control for factors that may have influenced crime rates. In addition, a fixed-effect regression model is calculated. However, there are repeated observations included in the data with crime rates calculated for the same census tracts over multiple years to compare effects pre- and post-implementation of the Opportunity Zones policy. A random-effects regression analysis might be more appropriate to account for the possible correlation in crime rates within these repeated measures. Another limitation is that there could be extreme differences in certain potential confounding factors between the Opportunity Zones and non-Opportunity Zones that are not adequately controlled for in the statistical model. In my difference-in-differences analysis, I did not match Opportunity Zone and non-Opportunity Zone census tracts, because I was concerned this would too severely limit my sample size and be difficult to carry out practically given that census tracts were selected as Opportunity Zones specifically because of their unique, struggling economies. These are concerns for future research to explore. The linear regression model conducted still provides a powerful approach to obtain useful insights into how Opportunity Zones impacted crime rates in Chicago.

## FINDINGS

This section will outline the results and conclusions extracted from the difference-in-differences analysis described above. Throughout the section, multiple maps, line plots, tables, and boxplots will be displayed to provide insight into how the Opportunity Zone policy impacted crime in Chicago. As mentioned above, these displays were created from a dataset deriving from American Community Survey, Internal Revenue Service, and City of Chicago data ("American Community Survey"; "Crimes – 2001 to Present – Map" 2022; IRS 2018). The goal of this quantitative analysis is to examine how economic development programs, like Opportunity Zones, impact crime rates, as demonstrated in this case study of Chicago.

Even though the literature review provided substantial context to the crime situation in Chicago, I wanted to further investigate the crime situation during my specific years of study

(2016 – 2020). Using the combined dataset described in the Methodology section, I produced the maps on the following pages (Figures 3 – 6), which show the total crime rate per census tract by year – 2016, 2017, 2019, and 2020 (2018 was not included because it is the year the policy was implemented in Chicago). In these maps, there is some missing data due to gaps in the crime and economic datasets used. Nonetheless, the maps visually render how total crime in Chicago decreased from 2016 to 2020 across the board. But, in certain high crime census tracts, total crime remained high. Notice how the census tract a little west of the Hyde Park neighborhood consistently had a total crime rate of about 500 crimes per 1,000 people, a tragically persistent high total crime rate. Also, notice how the higher total crime census tracts are generally located in the Southern and Western neighborhoods of Chicago, aligning with the placement of Opportunity Zones in Chicago (Appendix 2). These displays present a picture that is consistent with the literature review section and the Fatal and Non-Fatal Shooting Victimization statistics shared in the Crime in Chicago subsection. They also align with my initial expectation that crime in Chicago would be highly correlated to the disinvested communities located on the South and West sides of the city. Such presentations reveal the importance of studying Opportunity Zones and their effect on crime in Chicago – because these Zones directly correspond to the neighborhoods that have struggled with high crime rates for years.

**Figure 3:** Total Crime Rate in 2016 by Census Tract

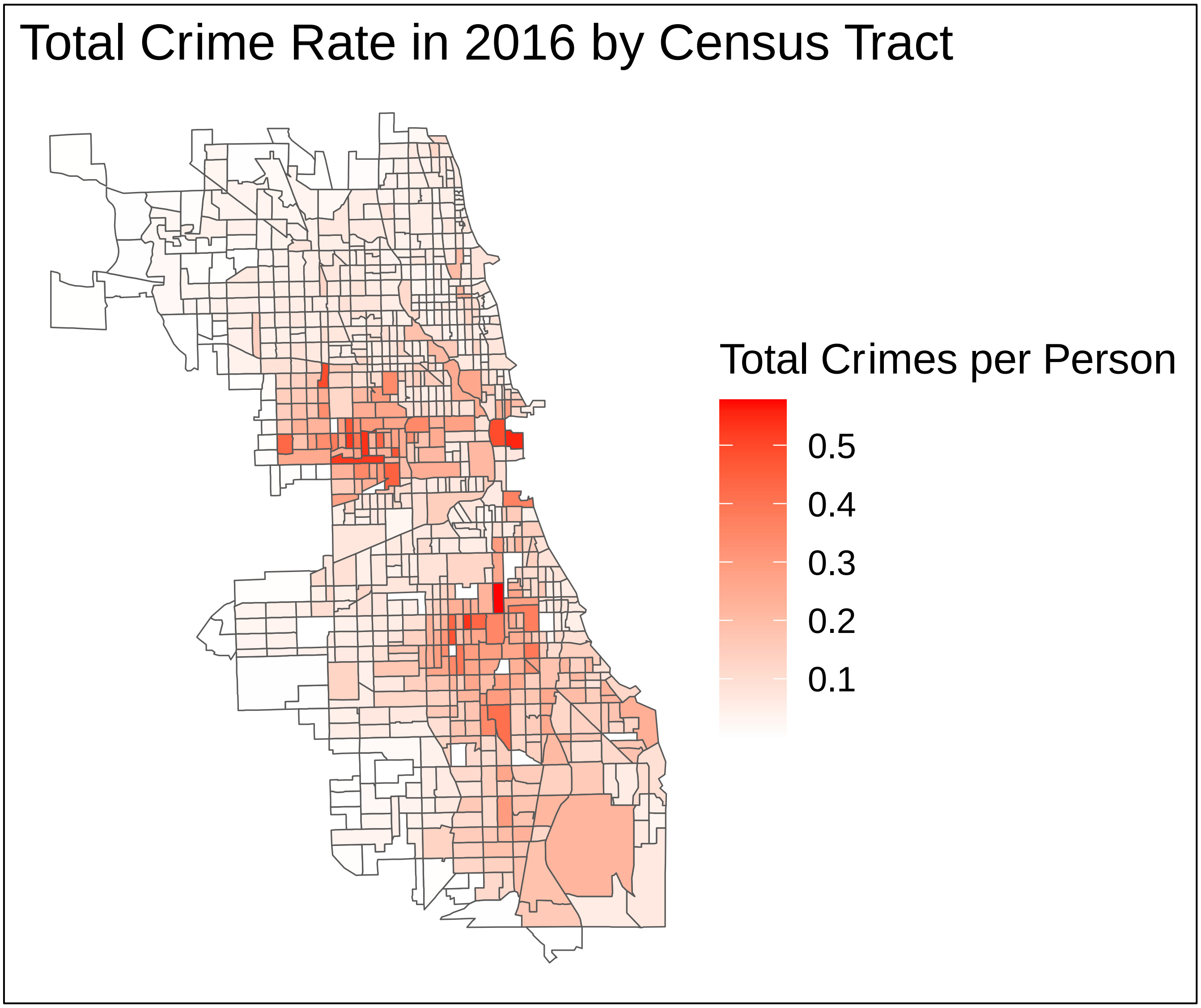


**Figure 4:** Total Crime Rate in 2017 by Census Tract

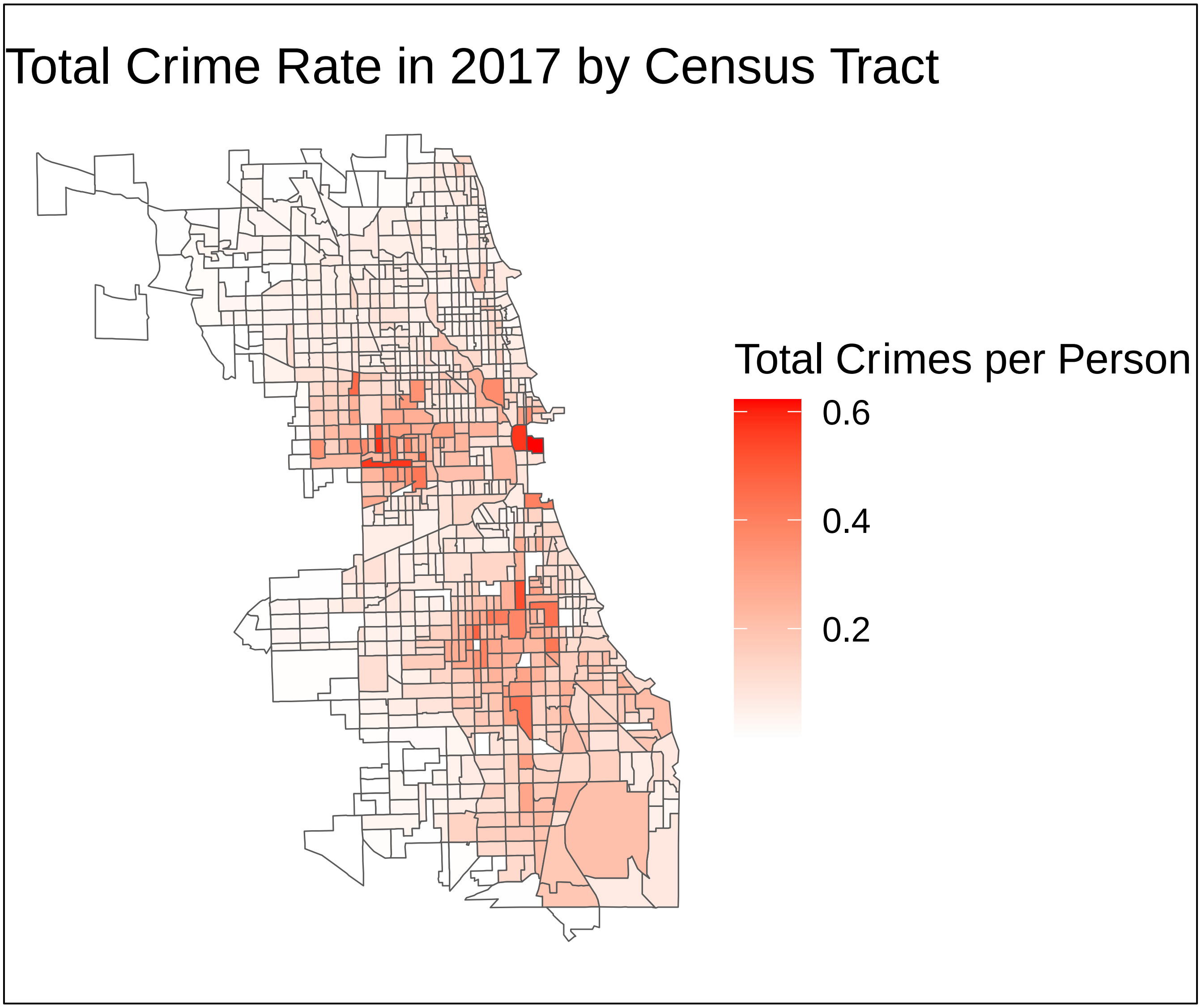


**Figure 5:** Total Crime Rate in 2019 by Census Tract

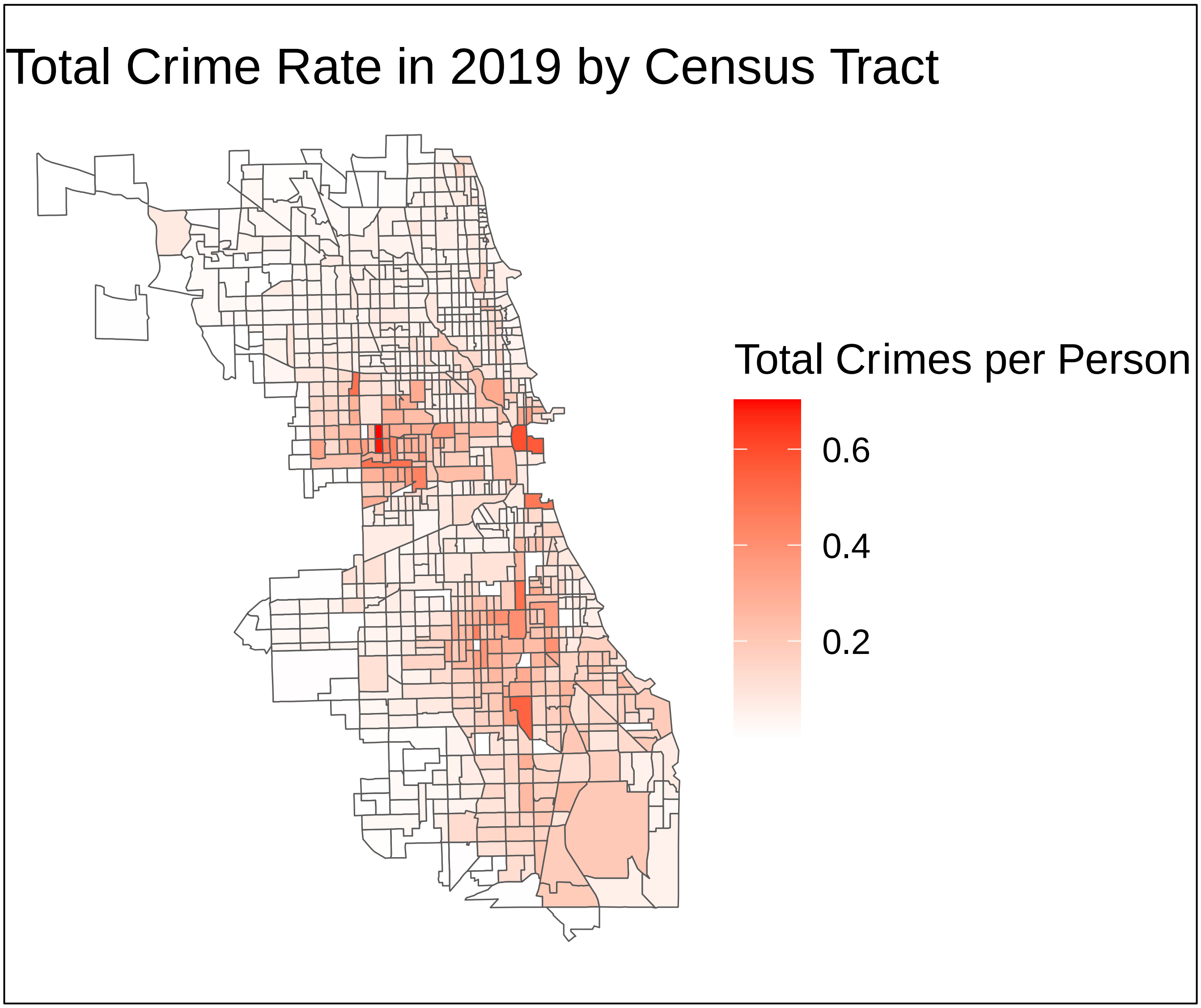
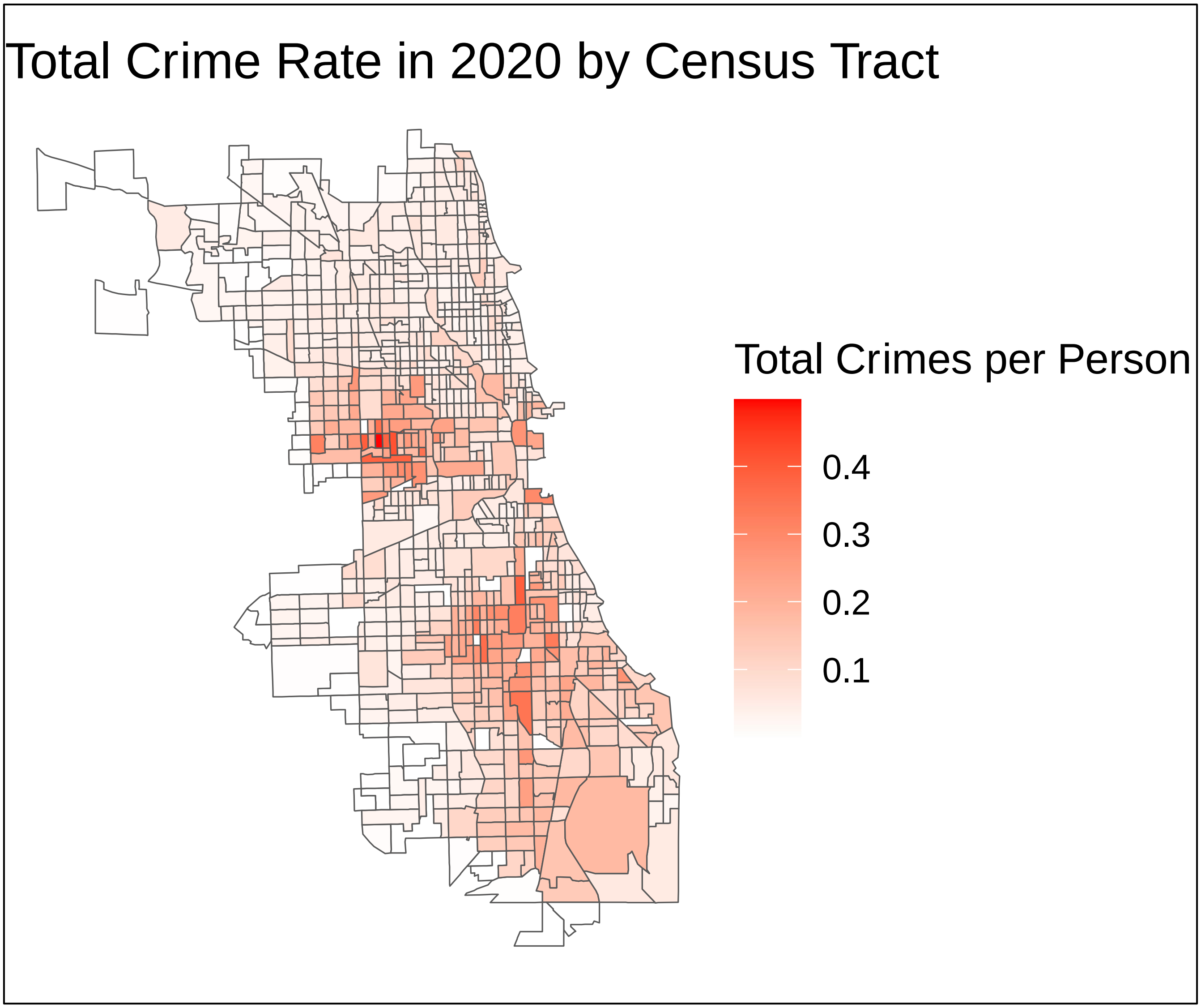
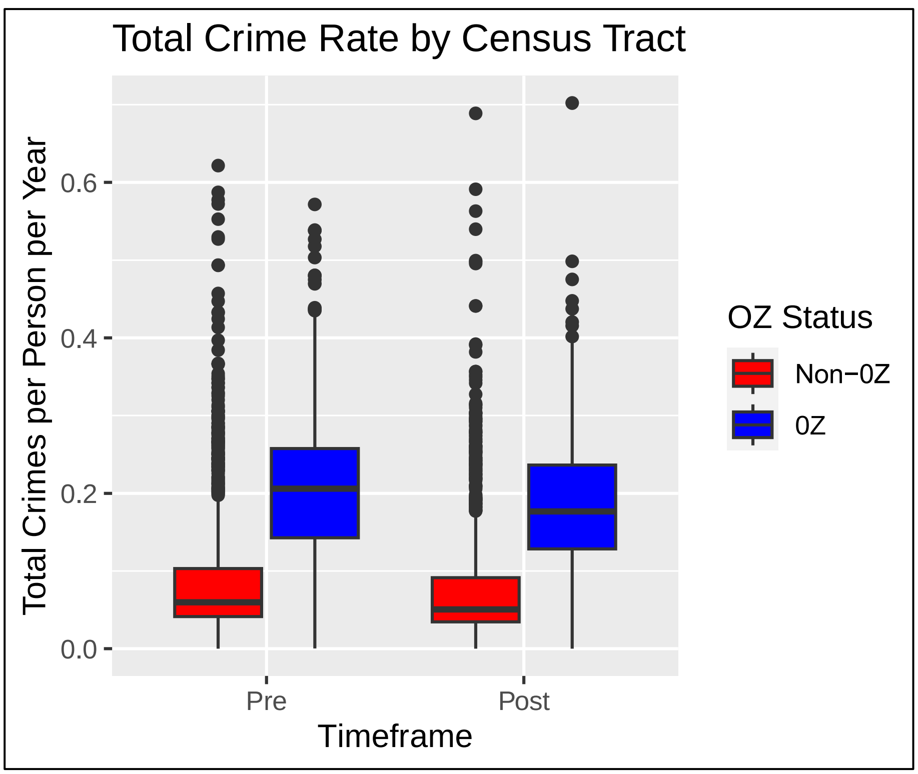


**Figure 6:** Total Crime Rate in 2020 by Census Tract




To further visually compare the crime rates in Opportunity Zone and non-Opportunity Zone census tracts, I created three boxplots (Figures 7 – 9) that illustrate the distribution of census tracts according to the total, violent, and non-violent crime rates calculated. These displays break down the comparisons of crime rates in non-Opportunity Zone and Opportunity Zone census tracts before and after the implementation of the policy, without controlling for other covariates. The pre and post implementation timeframes here include the crime rates for the years 2016–2017 (pre-implementation) and 2019–2020 (post-implementation). Each census tract is counted twice (for both years) in both the pre and post implementation columns on the boxplots. It is apparent from these boxplots that Opportunity Zone census tracts had higher rates of total, violent, and non-violent crime rates than non-Opportunity Zone census tracts both pre and post implementation. This is consistent with the conclusions reached by inspection of the maps in Figures 3 – 6 and in the literature review. After the implementation of the policy, there was a decrease in crime rates (including total, violent, and non-violent crime rates) in both Opportunity and non-Opportunity Zone census tracts. There is a more pronounced decrease in total and violent crime rates post-implementation in the Opportunity Zone census tracts, but it is not clear if this is significant. Furthermore, these boxplots do not account for possible confounding factors, so causality cannot be determined. [1]

**Figure 7:** Boxplot of Total Crime Rate by Census Tract




[1] OZ = Opportunity Zone and Non-OZ = non-Opportunity Zone (same meaning for each use throughout this analysis).

For example, using the interquartile range (IQR) on the Total Crime Rate Boxplot, the difference in estimated total crimes per person per year show this reduction. Opportunity Zone census tracts had an estimated mean of 200 total crime events per 1,000 people per year pre-implementation of the policy and an estimated mean of 180 total crime events per 1,000 people per year post-implementation. Non-Opportunity Zone census tracts, on the other hand, had an estimated mean of 55 total crime events per 1,000 people per year pre-implementation and an estimated mean of 45 crime events per 1,000 people per year post-implementation. Thus, these boxplots visually show there was more of a decrease in estimated crime rates in Opportunity Zone than non-Opportunity Zone census tracts, but it cannot be concluded that the Opportunity Zone policy caused this decrease without including controls.

**Figure 8:** Boxplot of Violent Crime Rate by Census Tract

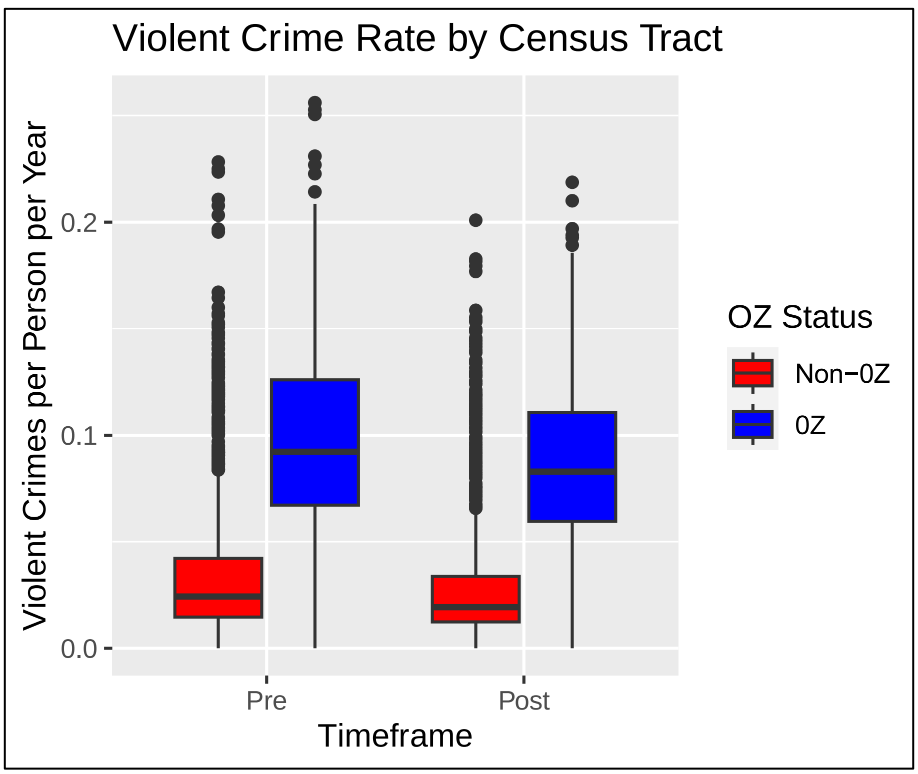
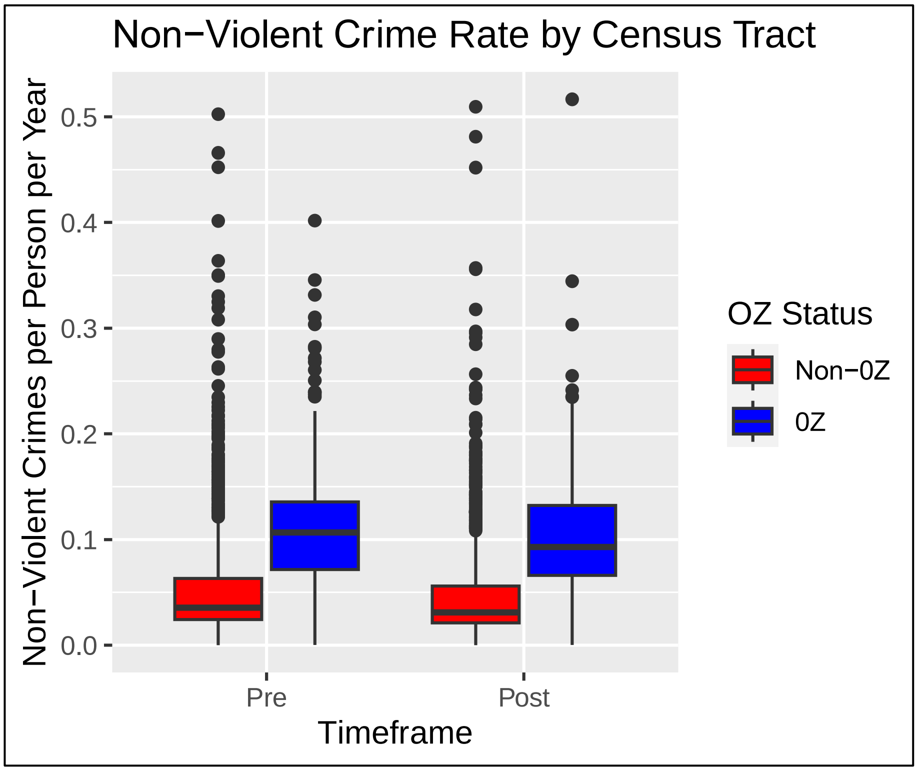


**Figure 9:** Boxplot of Non-Violent Crime Rate by Census Tract




It is not possible to draw firm conclusions about the implementation of Opportunity Zones from these boxplots because there are many differences between Opportunity Zones and non-Opportunity Zones that might confound any causal relationship with reducing crime rates over time. In fact, when I adjusted for American Community Survey data comparing Opportunity Zone and non-Opportunity Zone census tracts, there were many significant differences (Table 2). I examined covariates for economic, racial, educational, and inequality factors, and all were significantly different between Opportunity Zones and non-Opportunity Zones. As noted in the Methodology section, there are other factors, such as the COVID-19 pandemic that took storm in 2020, which also could have influenced the crime rates in

Opportunity Zones and non-Opportunity Zones. These were not considered here, but the covariates that were examined are important to consider.

**Table 2:** Covariates Used in Difference-in-Differences Model

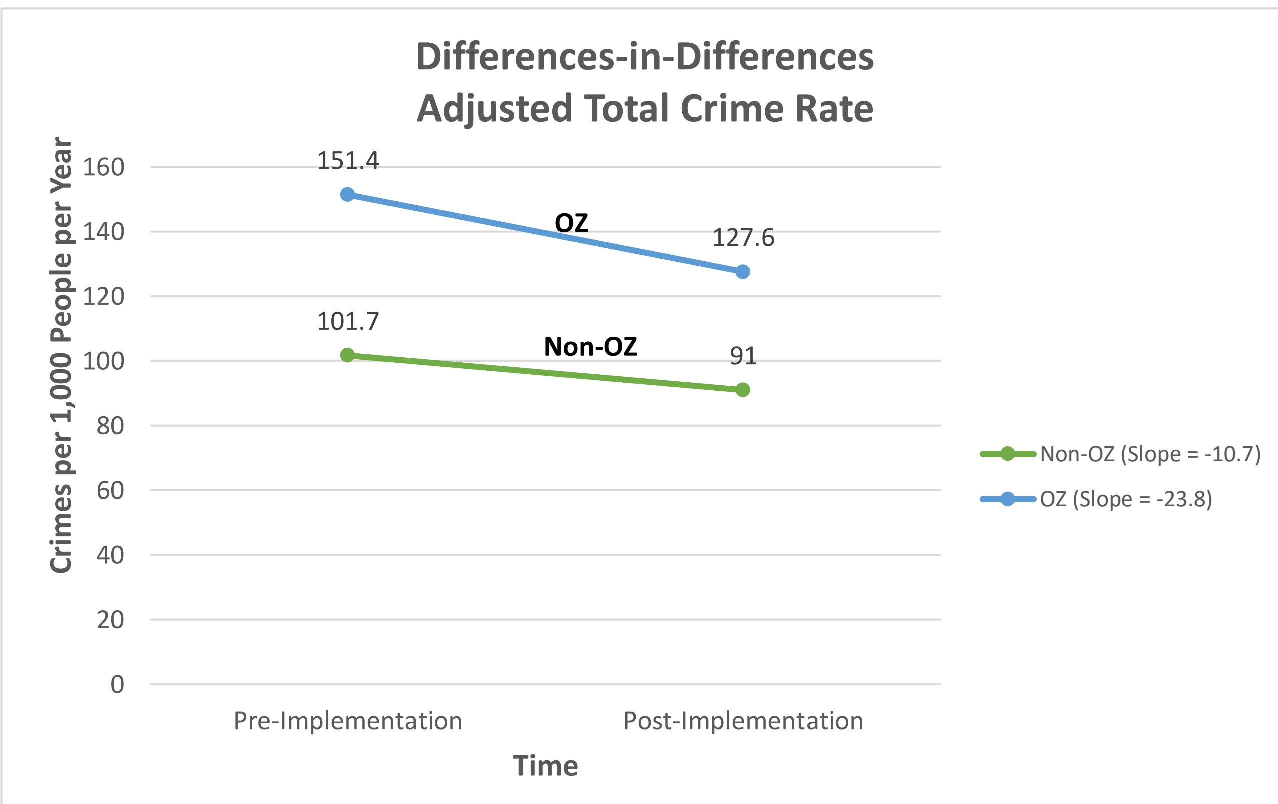
| ***Covariate Summary*** | ***OZ (n = how many census tracts are OZ)*** | ***Non-OZ (n = how many census tracts area Non-OZ)*** |
|---|---|---|
| *Mean Percent Non-White (SD)*[2]* | 9.57 (13.5) | 52.7 (28.4) |
| *Mean Percent Hispanic (SD)** | 13.3 (20.5) | 28.9 (28.7) |
| *Mean Young Adult Population Less than High School (SD)** | 18.3 (8.7) | 13.9 (11.2) |
| *Mean Median Household Income (Adjusted for 2020 Inflation) (SD)** | $33,419.4 ($12,960.56) | $70,775.45 ($35,440.56) |
| *Mean Gini Index (SD)** | 0.49 (0.08) | 0.45 (0.07) |

To control for these potential confounding differences between Opportunity Zones and non-Opportunity Zones, I carried out a linear regression analysis to test the difference-in-differences of the declining crime rates over time. The results of these models are visually shown in Figures 10 – 12 as line-plots that display the estimated average crime events per 1,000 people per year predicted by the model. The first plot (Figure 10) displays the average total crime rate adjusted for the covariates shown in Table 2, showing that there was more of a pronounced decrease in the average estimated total crime rate in Opportunity Zones than in non-Opportunity Zones, as shown by the slopes. The points here reflect the parameter estimates from the model. For example, 101.7 means that before the implementation of the Opportunity Zone policy, in the census tracts never designated as Opportunity Zones, the estimated average total crime events

[2] SD = Standard Deviation
[*] T-tests of differences in means between OZ and non-OZ were significant at $p < 0.05$.

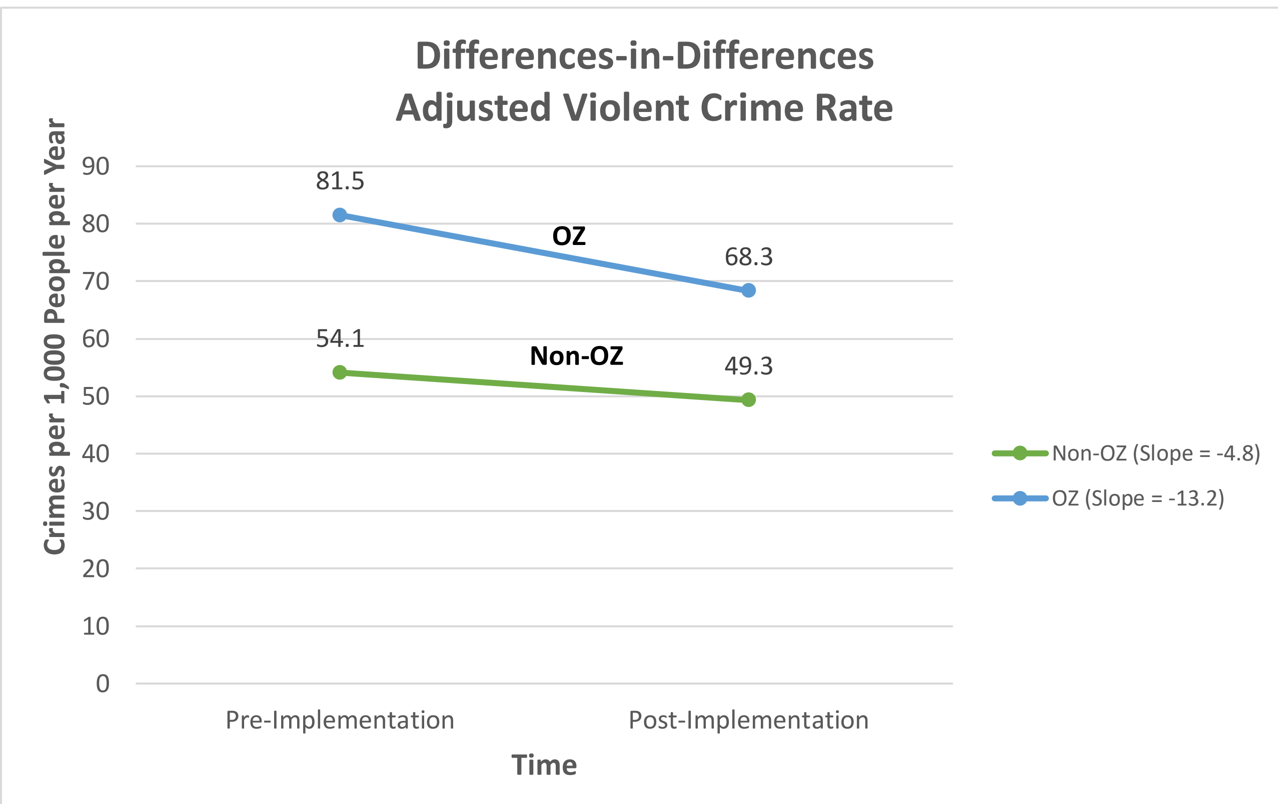
per 1,000 people per year were 101.7 incidents. The same logic follows for the rest of the points, and the slopes here represent the estimated change in average total crime rates for Opportunity Zone and non-Opportunity Zone census tracts. The difference in the slopes (OZ and non-OZ) calculates the "difference-in-differences", representing the interaction term and comparing the change in the average total crime rate pre vs. post implementation in Opportunity Zones and non-Opportunity Zones, which in this case is a decrease of 13.1 (or -13.1) total crime events per 1,000 people per year. This demonstrates that there was a significantly greater decrease in the total crime rate in Opportunity Zones compared to non-Opportunity Zones, meaning that there was not only an effect but a positive one in that the economic development program led to a decrease in total criminal activity.

**Figure 10:** Difference-in-Differences in Adjusted Total Crime Rate



A similar trend was observed for the estimated violent crime rates. The plot in Figure 11 follows the same structure and shows that there was significant decrease in the adjusted (controls included) estimated change of violent crime rates for Opportunity Zones. The interaction term here, which again compares the estimated change in adjusted violent crime rate pre vs. post implementation in Opportunity Zones and non-Opportunity Zones, is -8.4 violent crime events per 1,000 people per year, meaning that there was a significantly greater decrease in the number of violent crime incidents in Opportunity Zones compared to non-Opportunity Zones. These results show that the implementation of the Opportunity Zone policy not only had a significant positive effect on total crime but also on violent crime rates, which I would argue is more important because of the gravity and danger that violent criminal activity can cause.

**Figure 11:** Difference-in-Differences in Adjusted Violent Crime Rate



The last line-plot (Figure 12) displays the estimated adjusted non-violent crime rates calculated in the linear regression analysis. While these results are not significant, as shown in Table 3, the results are still important to consider because they show that the Opportunity Zone policy did not influence non-violent crimes like theft, trespassing, prostitution, narcotics, obscenity, arson, etc. (Appendix 1). This is important to consider when thinking about the intended consequences of the policy; it might be that economic development policies, like Opportunity Zones, should not be considered to decrease more minor crimes. Nonetheless, the line plot still shows that there was a decrease in the change in average non-violent crime incidents per 1,000 people per year. But, the interaction term's p-value was not significant, so we cannot conclude a causal relationship between the Opportunity Zone policy and the decrease in non-violent crime rates.

**Figure 12:** Difference-in-Differences in Adjusted Non-Violent Crime Rate

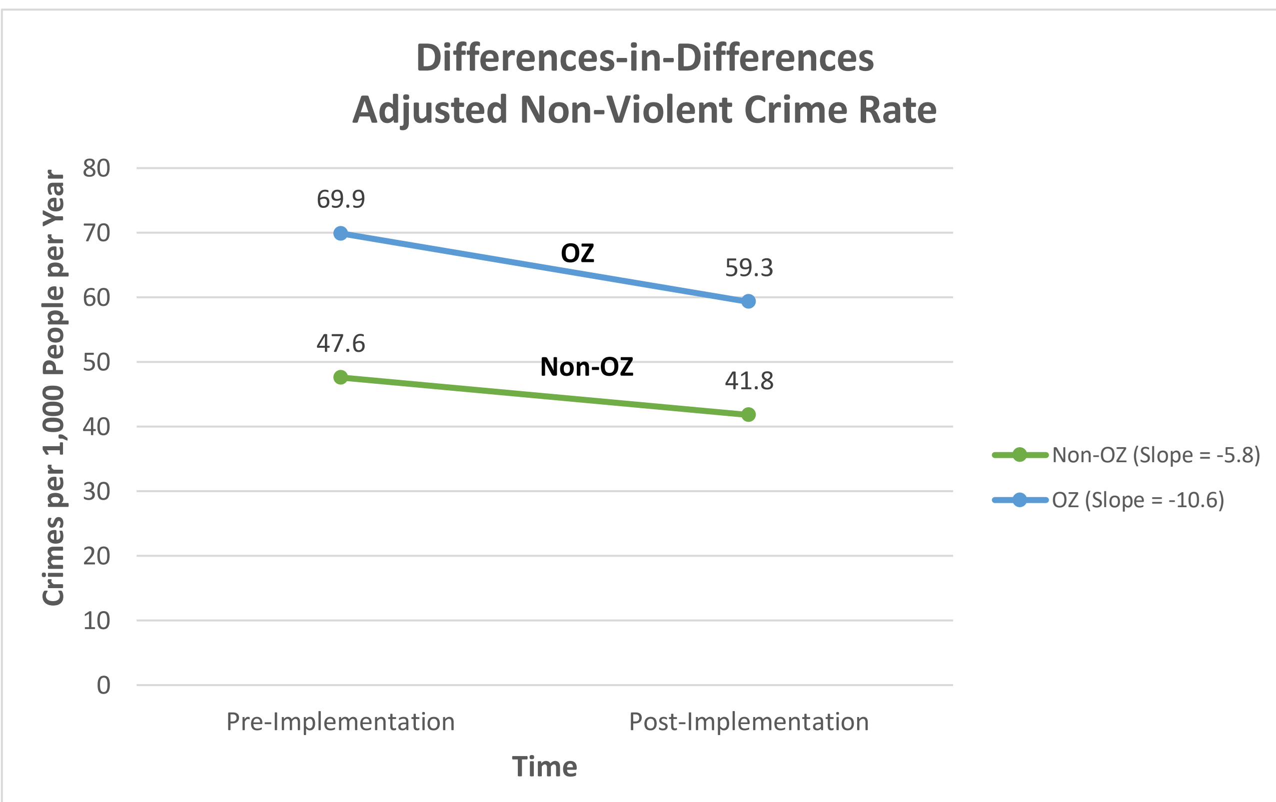


Table 3 presents the parameter estimates and their statistical significance from the linear regression models of the data, which were used to create the line plots. Again, adjusted here means that these estimates were based on models controlling for the potential confounders described in the Methodology section, whereas unadjusted means the models did not include these controlling variables. The “Opportunity Zones” column represents the $\beta_1$ parameter, which is the difference in average crime rate between non-Opportunity Zones and Opportunity Zones before the implementation of the policy. The “Time” column represents the $\beta_2$ parameter, which is the difference in average crime post-implementation minus pre-implementation for non-Opportunity Zones. Lastly, the “Opportunity Zones*Time” column represents the $\beta_3$ parameter, which is the difference between these differences over time, comparing the average crime rates in Opportunity Zones to non-Opportunity Zones. The parameter estimates are the first (non-parenthesized) number; the standard error estimates are displayed in the parentheses; and the p-value significance is indicted by the asterisks, one asterisk referring to a highly significant result.

**Table 3:** Statistical Analysis from Difference-in-Differences Model

| ***Results of Analysis*** | | ***Opportunity Zones*** | ***Time*** | ***Opportunity Zones*Time*** |
|---|---|---|---|---|
| *Total Crime Rate* | *Unadjusted* | 127.2 (5.5)*** | -10.7 (3.2)*** | -12.6 (7.8) |
| | *Adjusted* | 49.7 (5.1)*** | -10.7 (2.6)*** | -13.1 (6.5)* |
| *Violent Crime Rate* | *Unadjusted* | 65.6 (2.3)*** | -4.8 (1.3)** | -8.2 (3.3)* |
| | *Adjusted* | 27.5 (2.0)*** | -4.8 (1.0)*** | -8.4 (2.6)* |
| *Non-Violent Crime Rate* | *Unadjusted* | 61.5 (3.4)*** | -5.9 (2.0)** | -4.4 (4.8) |
| | *Adjusted* | 22.2 (3.3)*** | -5.9 (1.7)*** | -4.7 (4.3) |
| *P-Value Significance: ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05* | | | | |

These displays illustrate how the implementation of the Opportunity Zones policy had a positive effect on crime, meaning the policy's implementation led to a decrease in both total crime and violent crime that was greater in Opportunity Zone census tracts than in non-Opportunity Zone census tracts, as estimated by the models. Such results support the argument that economic development policies, like Opportunity Zones, which are implemented through the tax code, have a chance to reduce criminal activity. But, as with any policy, it is important to consider all unintended consequences or externalities if you will, because sometimes they can have positive and negative effects. In this case, the reduction in total and violent criminal activity is positive, which policymakers should consider when reviewing the validity of the Opportunity Zone program.

## POLICY RECOMMENDATIONS

While these results provide an argument for economic development, place-based policies, like Opportunity Zones, as the literature indicated, there are limitations with the policy that need to be reformed to get the most out of the program. These limitations include the lack of community engagement in investment decisions, the risk of gentrification, and the potential of investments being transplanted from one community to another. All of these faults center around the community, indicating that the community needs to become a key actor within the program. Nonetheless, even with these limitations, the results of the analysis above show that Opportunity Zones are still a worthwhile policy because of the unintentional benefits they can have on social issues like crime. Because of this, I would recommend the enactment of policies to reform the Opportunity Zone program and additional funding and resources from the city and state level to advance the program further in a localized fashion.

The case studies mentioned in the literature review describe how the design of the Opportunity Zone program leaves little room for community input into who receives investments and how. This leaves the investors with a lot of discretion, and the people who the investments directly impact no control. Such a setup is unethical and increases the chances of malpractice because investments made could negatively impact the local population and push them out (gentrification) or remove investments from a different community (disinvestment). To solve this, policymakers at the federal level could stipulate that for investors to receive the tax break on their capital gains, they would need proof of community engagement. This proof could come in the form of collaboration records with a local non-profit, business association, school, or governmental institution. By engaging with the community, concerns about gentrification and the disinvestment of resources from other communities will be addressed. Residents would be allowed to share insights into how the investment will change their or other communities. But this is only one step in the reform process. Like any policy, there needs to be oversight and review of the implementation to ensure that the reforms are being successfully carried out. This oversight could be required by the IRS tax policy, in which it could also be stipulated that proof of community collaboration needs to occur every tax year, so that this is a continual mandate and not a one-and-done requirement. Hopefully, this would encourage continuous community engagement and oversight of the investment plan.

In addition to this reform, I would also recommend that the city and state investigate local pathways and resources for additional economic development programs. The results of my analysis show that the Opportunity Zone program had a significant, positive effect in reducing total and violent crime rates, revealing that economic development, place-based policies are a viable solution to reduce criminal activity. Because of this, city and state governments should create and implement more local economic development policies to reduce crime and spur economic opportunity. For example, at the state level, Illinois could provide additional resources to the already existing R3 grant program, which provides grant funding to communities that have been “harmed by violence, excessive incarceration, and economic disinvestment”. To receive funding from this grant program, individuals must reside or work in specific designated areas (State of Illinois). Even though this R3 program provides economic stimulus through grants, it is very similar in theory to the federal Opportunity Zone program, because it is an economic development, place-based policy. This program is just one avenue in which the state can provide additional funding and economic support through. The state and city could also create a similar tax structure to the Opportunity Zone program and provide tax breaks. These are just some policy ideas where the local government could provide additional economic assistance. The hope is that through greater economic support, historically disinvested communities will gain economic opportunities that will not only increase the economic health of the area, but also lead to a decrease in crime rates, as projected by my model.

Such positive effects, provide ample argument for more place-based, economic development programs, but as mentioned earlier, the implementation and reform of these programs will be essential to the success of the policies.

## CONCLUSION

This analysis demonstrates that the Opportunity Zone policy led to a decrease in the estimated total and violent crime rates in Qualified Opportunity Zones in Chicago, suggesting that economic development, place-based policies like Opportunity Zones could be viable solution to reduce crime in Chicago. Nonetheless, it is important to consider the research that has already been conducted on Opportunity Zones, which shows that there is a need for reform within the policy to engage more with disinvested community members. Through additional reforms and increased funding and support, the Opportunity Zone policy, and others like it, have a chance to revitalize communities, increasing safety and bringing in more economic opportunity.

While this study fills a gap within the literature by examining the effects Opportunity Zones have on crime in Chicago, additional research still needs to be done. Future research should continue to improve my model by utilizing a randomized-effect regression analysis and by removing other possible confounders. In addition, researchers should explore the impacts placed-based economic development programs, like Opportunity Zones, have on other social issues. The possibilities are endless, but the Opportunity Zone policy could also have unintentionally influenced the health, housing, education, and transportation of a city. Lastly, researchers should explore other ways the tax code could be used to advance economic development programs like the Opportunity Zone policy. The tax code offers an easily implementable and uniform vehicle for policy reform that should not be overlooked. This is only the beginning for place-based policies and their transformational effects. With the right intention and implementation plan, these policies have the potential to make our society safer and more prosperous.

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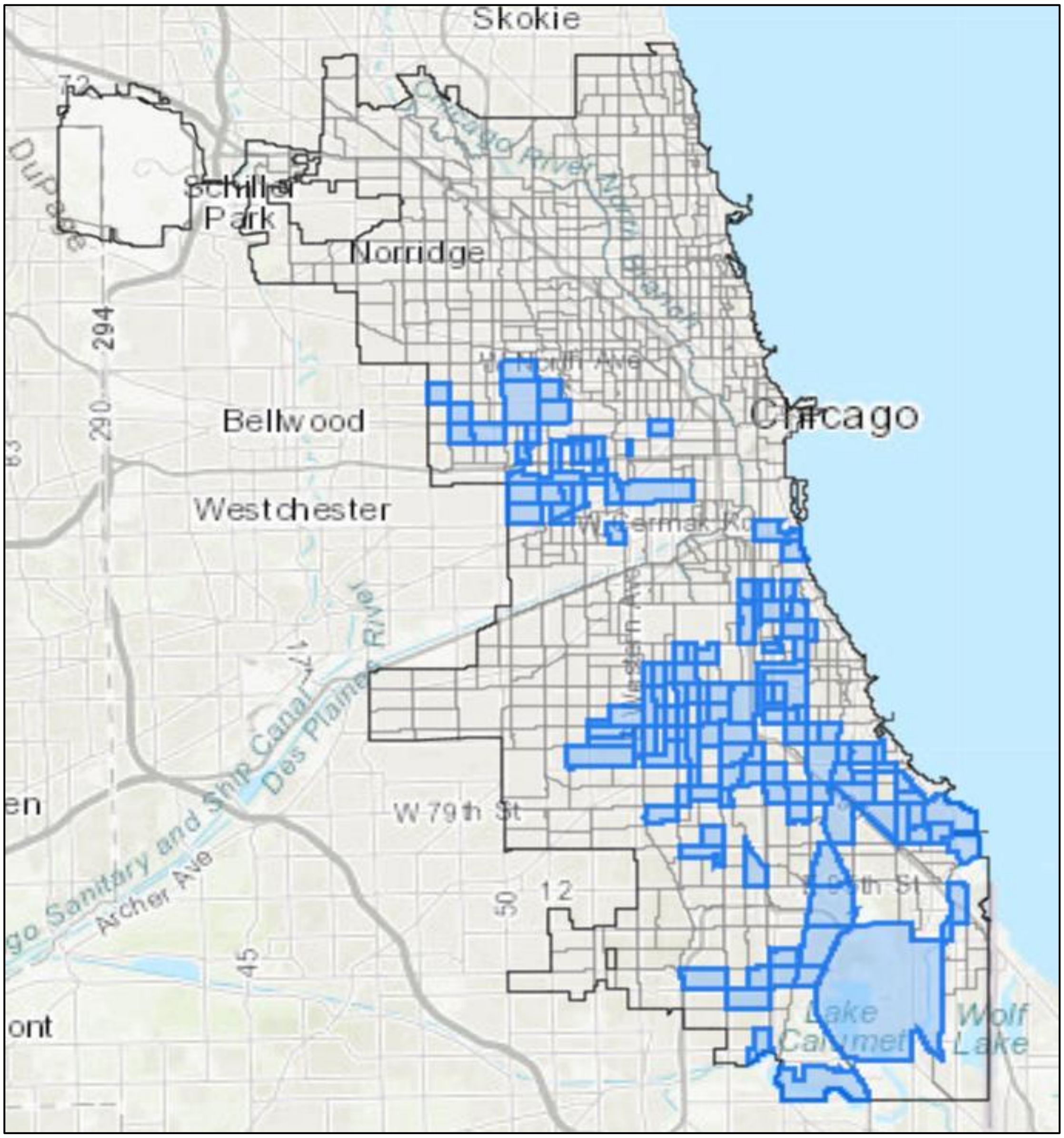
# APPENDICES

**Appendix 1:** Table of Violent and Non-Violent Crimes as Classified by the FBI ("FBI: UCR")

| Considered Violent Crimes | Considered Non-Violent Crimes |
|---|---|
| Motor Vehicle Theft | Theft |
| Assault | Deceptive Practice |
| Battery | Criminal Damage |
| Robbery | Other Offense |
| Burglary | Narcotics |
| Criminal Sexual Assault | Weapons Violation |
| Sex Offense | Criminal Trespass |
| Kidnapping | Interference with Public Officer |
| Human Trafficking | Arson |
| Homicide | Prostitution |
| | Offense Involving Children |
| | Public Peace Violation |
| | Liquor Law Violation |
| | Stalking |
| | Concealed Carry License Violation |
| | Gambling |
| | Intimidation |
| | Non-Criminal (Subject Specified) |
| | Obscenity |
| | Non-Criminal |
| | Other Narcotic Violation |
| | Public Indecency |
| | Ritualism |

**Appendix 2:** Map of the City of Chicago divided by census tracts. The blue, highlighted census tracts are designated Opportunity Zones (City of Chicago 2022).



**Appendix 3:** For replicability purposes, below is an outline of the coding I conducted for my difference-in-differences analysis. It is important to note that this code does not include the steps used to generate the line-plots in the Findings section. These line-plots were created using the datapoints generated from my model but were designed in Excel. The code is colored in red, and a description of each step is in black.

Installed readr package to read in crime data. Then, set working directory.

```
install.packages("readr")
getwd()
# "/Users/gracezandi/Desktop/UChicago 2019-2023/UChicago 2022-2023/BA Thesis Seminar/Data Files/Quant Analysis" #
```

Read in crime date from the City of Chicago, which was downloaded to my working directory.

```
crime <- read.csv("/Users/gracezandi/Desktop/UChicago 2019-2023/UChicago 2022-2023/BA Thesis Seminar/Data Files/Quant Analysis/CDP_2001-Present_No_CT_20221226.csv")
crime
```

Installed sf and dplyr packages.

```
install.packages("sf")
install.packages("dplyr")
library(sf)
library(dplyr)
```

Used these packages to pinpoint where crime event in the crime dataset using the longitude and latitude provided. Then, used these coordinates to match with the corresponding census tract in Cook County using a shape file.

```
census_tracts <- st_read("cb_2018_17_tract_500k.shp", quiet = TRUE)
crime_sf <- crime %>%
  filter(!is.na(Latitude), !is.na(Longitude)) %>%
  st_as_sf(coords = c("Longitude", "Latitude"), crs = st_crs(census_tracts))
intersected <- st_intersects(crime_sf, census_tracts)
crime_census <- crime_sf %>%
  mutate(intersection = as.integer(intersected),
         fips = if_else(is.na(intersection), "",
                        census_tracts$GEOID[intersection]))
View(crime_census)
```

Using the new crime_census dataset, I filtered for the years 2016-2020 because those are the intended years of study.

```
crime_censuswork <- crime_census %>% filter(Year==2016 | Year==2017 | Year==2018 | Year==2019 | Year==2020)
View(crime_censuswork)
```

Then assigned 1 for the calculation of total crime.

```
crime_censuswork$totcrime <- 1
```

Got rid of geometry column that was assigned in the SF package.

```
crime_censusworknog <- st_set_geometry(crime_censuswork,NULL)
View(crime_censusworknog)
```

To find the categories in the Primary Type column, I used the unique command.

```
unique(crime_censusworknog[c("Primary.Type")])
```

Found violent and non-violent crime counts.

```
crime_censusworknog$vcrime <- ifelse(crime_censusworknog$Primary.Type=="MOTOR VEHICLE THEFT" | crime_censusworknog$Primary.Type=="BATTERY" |
crime_censusworknog$Primary.Type=="ASSAULT" |
crime_censusworknog$Primary.Type=="ROBBERY" |
crime_censusworknog$Primary.Type=="BURGLARY" |
crime_censusworknog$Primary.Type=="CRIM SEXUAL ASSAULT" |
crime_censusworknog$Primary.Type=="CRIMINAL SEXUAL ASSAULT" |
crime_censusworknog$Primary.Type=="SEX OFFENSE" |
crime_censusworknog$Primary.Type=="KIDNAPPING" |
crime_censusworknog$Primary.Type=="HUMAN TRAFFICKING" |
crime_censusworknog$Primary.Type=="HOMICIDE", 1, 0)
crime_censusworknog$nvcrime <- ifelse(crime_censusworknog$totcrime==1 &
crime_censusworknog$vcrime==0, 1, 0)
```

Aggregated total, violent, non-violent crimes by year and by census tract

```
crime_aggregate <- crime_censusworknog %>% group_by(fips, Year) %>%
summarize(totcrimen = sum(totcrime), vcrimen = sum(vcrime), nvcrimen = sum(nvcrime))
```

Filled out the blank census tracts to NA and filtered them out so only filled in the dataset remained.

```
crime_aggregatet3 <- replace(crime_aggregate, crime_aggregate==", NA)
crime_aggregatefilter <- crime_aggregatet3 %>% filter(!is.na(fips))
```

Merged the crime dataset (that now had census tracts and crime rate information) with the OZ and ACS datasets.

Read in OZ and ACS data.

```
OZ <- read.csv("/Users/gracezandi/Desktop/UChicago 2019-2023/UChicago 2022-2023/BA Thesis Seminar/Data Files/Quant Analysis/IRS_CookCounty_OZ_20221228.csv")
ACSnoOZ <- read.csv("/Users/gracezandi/Desktop/UChicago 2019-2023/UChicago 2022-2023/BA Thesis Seminar/Data Files/Quant Analysis/ACS_2016-2020_No_OZ_20221226_Edited.csv")
```

Left joined ACS data w/o OZ to the OZ data to create the final ACS dataset.

```
ACS <- left_join(ACSnoOZ, OZ, by = c("fips" = "fips"))
```

Checked this join-ment.

table(ACS$OZ)

```
ACS %>% count(OZ)
OZsix <- anti_join(OZ, ACSnoOZ, by = c("fips" = "fips"))
```

Changed NA in OZ data to 0.

```
ACS["OZ"][is.na(ACS["OZ"])] <- 0
ACS = subset(ACS, select = -c(OZnoNA))
```

Changed fips "characters" to numbers in both crime and ACS combined data.

```
crime_aggregatefilter$fips = as.numeric(as.character(crime_aggregatefilter$fips))
ACS$fips = as.numeric(as.character(ACS$fips))
```

Left joined the crime_aggregatefilter and ACS data to create a new DF mydata.

mydata <- left_join(crime_aggregatefilter, ACS, by = c("fips" = "fips"))

Checked the join-ment.

```
table(mydata$OZ)
mydata_censustracts <- mydata %>% count(OZ)
ACS_LOcensustracts <- anti_join(ACS, crime_aggregatefilter, by = c("fips" = "fips"))
```

Exported crime_censusworknog into a CSV.

```
write.csv(crime_censusworknog, "~/crime_censusworknog.csv")
```

Created a new variable for Total Population to account for missing data.

```
mydata$TotalPopX <- mydata$TotalPop
mydata["TotalPopX"][mydata["TotalPopX"] == 0] <- NA
```

Created new variables for crime rates (total crime, violent crime, non-violent crime / TotalPopX).

```
mydata$totcrimer <- mydata$totcrimen / mydata$TotalPopX
mydata$vcrimer <- mydata$vcrimen / mydata$TotalPopX
mydata$nvcrimer <- mydata$nvcrimen / mydata$TotalPopX
```

Removed a few unnecessary columns from the ACS data because there is a limit of 50 columns.

```
mydata = subset(mydata, select = -c(State, County))
mydata = subset(mydata, select = -c(AreaName))
```

Created a new variable for time that labeled 2016 & 2017 as 0 (pre-implementation) and 2019 & 2020 as 1 (post-implementation) and removed 2018 as NA

```
mydata$time <- ifelse((mydata$Year==2016) | (mydata$Year==2017), 0,
ifelse((mydata$Year==2019) | (mydata$Year==2020), 1, NA))
```

Conducted a Statistical Analysis.

Model 1 (totcrimer)

```
model.1 <- lm(totcrimer ~ OZ, data = mydata)
summary(model.1)
```

Model 2

```
model.2 <- lm(totcrimer ~ OZ + time, data = mydata)
summary(model.2)
```

Model 3

```
model.3 <- lm(totcrimer ~ OZ*time, data = mydata)
summary(model.3)
```

Model 4 (began controlling)

```
model.4 <- lm(totcrimer ~ OZ + PercentTotalPopWhiteAlone +
PercentTotalPopulationHispanicOrLatino + PercentPop25YearsAndOverLessThanHighSchool +
MedianHouseholdIncomeIn2020InflationAdjustedDollars + GiniIndex, data = mydata)
summary(model.4)
```

Model 5

```
model.5 <- lm(totcrimer ~ OZ*time + PercentTotalPopWhiteAlone +
PercentTotalPopulationHispanicOrLatino + PercentPop25YearsAndOverLessThanHighSchool +
MedianHouseholdIncomeIn2020InflationAdjustedDollars + GiniIndex, data = mydata)
summary(model.5)
```

Model 6 (vcrimer)

```
model.6 <- lm(vcrimer ~ OZ*time, data = mydata)
summary(model.6)
```

Model 7

```
model.7 <- lm(vcrimer ~ OZ*time + PercentTotalPopWhiteAlone +
PercentTotalPopulationHispanicOrLatino + PercentPop25YearsAndOverLessThanHighSchool +
MedianHouseholdIncomeIn2020InflationAdjustedDollars + GiniIndex, data = mydata)
summary(model.7)
```

Model 8 (nvcrimer)

```
model.8 <- lm(nvcrimer ~ OZ*time, data = mydata)
summary(model.8)
```

Model 9

```
model.9 <- lm(nvcrimer ~ OZ*time + PercentTotalPopWhiteAlone +
PercentTotalPopulationHispanicOrLatino + PercentPop25YearsAndOverLessThanHighSchool +
MedianHouseholdIncomeIn2020InflationAdjustedDollars + GiniIndex, data = mydata)
summary(model.9)
```

Exported and saved results.

```
write.csv(mydata, "~/mydata.csv")
```

Began graphing of boxplots and maps.

Boxplots were created using a copy of the dataset (mydata_copy2box), where I removed all NA data and created time and OZ columns as factors for data manipulation purposes.

```
mydata_copy2box <- na.omit(mydata_copy2)
mydata_copy2box$timefac <- as.factor(mydata_copy2box$time)
mydata_copy2box$OZfac <- as.factor(mydata_copy2box$OZ)
levels(mydata_copy2box$OZfac)[levels(mydata_copy2box$OZfac)=="0"] <- "Non-0Z"
levels(mydata_copy2box$OZfac)[levels(mydata_copy2box$OZfac)=="1"] <- "0Z"
levels(mydata_copy2box$timefac)[levels(mydata_copy2box$timefac)=="0"] <- "Pre"
levels(mydata_copy2box$timefac)[levels(mydata_copy2box$timefac)=="1"] <- "Post"
```

Created Total Crime Rate boxplot.

```
ggplot(mydata_copy2box, aes(x=timefac, y=totcrimer, fill=OZfac)) +
  geom_boxplot() +
  scale_fill_manual(values = c("red", "blue")) +
  ggtitle("Total Crime Rate by Census Tract") +
  xlab("Timeframe") + ylab("Total Crimes per Person per Year") +
  labs(fill = "OZ Status")
```

Created Violent Crime Rate boxplot.

```
ggplot(mydata_copy2box, aes(x=timefac, y=vcrimer, fill=OZfac)) +
  geom_boxplot() +
  scale_fill_manual(values = c("red", "blue")) +
  ggtitle("Violent Crime Rate by Census Tract") +
  xlab("Timeframe") + ylab("Violent Crimes per Person per Year") +
  labs(fill = "OZ Status")
```

Created Non-Violent Crime Rate boxplot.

```
ggplot(mydata_copy2box, aes(x=timefac, y=nvcrimer, fill=OZfac)) +
  geom_boxplot() +
  scale_fill_manual(values = c("red", "blue")) +
  ggtitle("Non-Violent Crime Rate by Census Tract") +
  xlab("Timeframe") + ylab("Non-Violent Crimes per Person per Year") +
  labs(fill = "OZ Status")
```

Installed packages again or checked for packages for mapping purposes.

```
install.packages(c("sf", "ggplot2", "dplyr"))
library(sf)
library(ggplot2)
library(dplyr)
```

Used a shapefile to get the census tracts of Cook County to map.

mtracts <- st_read("cb_2018_17_tract_500k.shp")
Used mydata_copy2 of final dataset for mapping purposes.
mydata_copy2 <- read.csv("mydata_20230407.csv")
mydata_copy2 <- rename(mydata_copy2, GEOID = fips)
Created map for 2016
mydata_2016 <- mydata_copy2[mydata_copy2$Year == 2016, ]
Changed "fips" column to "GEOID"
mydata_2016$GEOID <- as.character(mydata_2016$GEOID)
Left joined mtracts shapefile with 2016 cleaned data (removed all NAs)
mtracts <- left_join(mtracts, mydata_2016, by = "GEOID")
mtracts_chi2 <- na.omit(mtracts)
Generated map

```
ggplot(mtracts_chi2) +
  geom_sf(aes(fill = totcrimer)) +
  scale_fill_gradient(low = "white", high = "red") +
  labs(title = "Total Crime Rate in 2016 by Census Tract", fill = "Total Crimes per Person") +
  theme_void()
```

Used the same process as 2016 for map of 2017 data.

```
mtracts2017 <- st_read("cb_2018_17_tract_500k.shp") # think we already have with the census_tracts file #
mydata_2017 <- mydata_copy2[mydata_copy2$Year == 2017, ] # change this for every year #
mydata_2017$GEOID <- as.character(mydata_2017$GEOID)
mtracts2017 <- left_join(mtracts2017, mydata_2017, by = "GEOID") # would need to change the variable name in mydata_copy2 from fips to GEOID #
mtracts_chi2017 <- na.omit(mtracts2017)
```

Generated map for 2017

```
ggplot(mtracts_chi2017) +
  geom_sf(aes(fill = totcrimer)) +
  scale_fill_gradient(low = "white", high = "red") +
  labs(title = "Total Crime Rate in 2017 by Census Tract", fill = "Total Crimes per Person") +
  theme_void()
```

Used the same process as 2017 for map of 2019 data.

```
mtracts2019 <- st_read("cb_2018_17_tract_500k.shp") # think we already have with the census_tracts file #
mydata_2019 <- mydata_copy2[mydata_copy2$Year == 2019, ] # change this for every year #
mydata_2019$GEOID <- as.character(mydata_2019$GEOID)
mtracts2019 <- left_join(mtracts2019, mydata_2019, by = "GEOID") # would need to change the variable name in mydata_copy2 from fips to GEOID #
mtracts_chi2019 <- na.omit(mtracts2019)
```

Generated map for 2019

```
ggplot(mtracts_chi2019) +
  geom_sf(aes(fill = totcrimer)) +
  scale_fill_gradient(low = "white", high = "red") +
  labs(title = "Total Crime Rate in 2019 by Census Tract", fill = "Total Crimes per Person") +
  theme_void()
```

Used the same process as 2019 for map of 2020 data.

```
mtracts2020 <- st_read("cb_2018_17_tract_500k.shp") # think we already have with the
census_tracts file #
mydata_2020 <- mydata_copy2[mydata_copy2$Year == 2020, ] # change this for every year #
mydata_2020$GEOID <- as.character(mydata_2020$GEOID)
mtracts2020 <- left_join(mtracts2020, mydata_2020, by = "GEOID") # would need to change the
variable name in mydata_copy2 from fips to GEOID #
mtracts_chi2020 <- na.omit(mtracts2020)
```

Generated map for 2020

```
ggplot(mtracts_chi2020) +
  geom_sf(aes(fill = totcrimer)) +
  scale_fill_gradient(low = "white", high = "red") +
  labs(title = "Total Crime Rate in 2020 by Census Tract", fill = "Total Crimes per Person") +
  theme_void()
```

For the table with the covariates, I used a copy of the dataset to for just the year of 2016, as a standard, to calculate the mean and standard deviation for each covariate.

```
mydata_tp1 <- mydata_copy2[mydata_copy2$Year == 2016, ]
mydata_tp2 <- na.omit(mydata_tp1)
```

PercentTotalPopWhiteAlone

```
mean(mydata_tp2[mydata_tp2$OZ == '1', 'PercentTotalPopWhiteAlone'])
sd(mydata_tp2[mydata_tp2$OZ == '1', 'PercentTotalPopWhiteAlone'])
mean(mydata_tp2[mydata_tp2$OZ == '0', 'PercentTotalPopWhiteAlone'])
sd(mydata_tp2[mydata_tp2$OZ == '0', 'PercentTotalPopWhiteAlone'])
```

PercentTotalPopulationHispanicOrLatino

```
mean(mydata_tp2[mydata_tp2$OZ == '1', 'PercentTotalPopulationHispanicOrLatino'])
sd(mydata_tp2[mydata_tp2$OZ == '1', 'PercentTotalPopulationHispanicOrLatino'])
mean(mydata_tp2[mydata_tp2$OZ == '0', 'PercentTotalPopulationHispanicOrLatino'])
sd(mydata_tp2[mydata_tp2$OZ == '0', 'PercentTotalPopulationHispanicOrLatino'])
```

PercentPop25YearsAndOverLessThanHighSchool

```
mean(mydata_tp2[mydata_tp2$OZ == '1', 'PercentPop25YearsAndOverLessThanHighSchool'])
sd(mydata_tp2[mydata_tp2$OZ == '1', 'PercentPop25YearsAndOverLessThanHighSchool'])
mean(mydata_tp2[mydata_tp2$OZ == '0', 'PercentPop25YearsAndOverLessThanHighSchool'])
sd(mydata_tp2[mydata_tp2$OZ == '0', 'PercentPop25YearsAndOverLessThanHighSchool'])
```

MedianHouseholdIncomeIn2020InflationAdjustedDollars

```
mean(mydata_tp2[mydata_tp2$OZ == '1',
'MedianHouseholdIncomeIn2020InflationAdjustedDollars'])
sd(mydata_tp2[mydata_tp2$OZ == '1',
'MedianHouseholdIncomeIn2020InflationAdjustedDollars'])
mean(mydata_tp2[mydata_tp2$OZ == '0',
'MedianHouseholdIncomeIn2020InflationAdjustedDollars'])
sd(mydata_tp2[mydata_tp2$OZ == '0',
'MedianHouseholdIncomeIn2020InflationAdjustedDollars'])
```

GiniIndex

```
mean(mydata_tp2[mydata_tp2$OZ == '1', 'GiniIndex'])
sd(mydata_tp2[mydata_tp2$OZ == '1', 'GiniIndex'])
mean(mydata_tp2[mydata_tp2$OZ == '0', 'GiniIndex'])
sd(mydata_tp2[mydata_tp2$OZ == '0', 'GiniIndex'])
```