Equity vs. Predation:

Third-Party Enforcement of the Chicago Wheel Tax

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Abstract

In 2012 the City of Chicago sought to raise revenue by increasing compliance with the City's Wheel Tax Program. City leaders believed the most equitable way to pursue this objective would be by slightly increasing the price of the tax, nearly doubling the penalty for noncompliance, and increasing strategic enforcement. Other studies have examined Chicago's ticketing practices around the time and determined the City's actions disproportionately impacted low-income and minority residents. Though these studies raise many concerns regarding the *outcomes* of ticketing practices, they are less conclusive on the originators themselves.

This paper seeks to explore differences in enforcement between units that would constitute inequitable policy implementation at the street-level. I utilize a difference-in-difference approach to analyze the ticketing practices of a contracted third-party ticketing unit, Serco, relative to units under the authority of the County Clerk's Office and the Department of Finance to determine if the 2012 change led to more aggressive enforcement of the Wheel Tax Program when controlling for common transportation equity indicators. I find that areas where City of Chicago units are the primary enforcer experienced a greater increase in penalties relative to Serco, which is consistent with the prevailing literature on transportation inequity in Chicago.

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1. Introduction

Roughly three million Chicagoans rely on the city's transportation systems of roads, public buses and trains, and waterways for access to social networks, leisure activities, and, perhaps most importantly, their places of employment on a nearly daily basis. Policymakers have long claimed that transportation equity is an important factor for facilitating sustainable growth in Chicago, however, multiple studies since 2018 have found that the ticketing practices in Chicago, which serve as a substantial source of funding for this transportation system, is aggressive at its best, and regressive at its worst.

A June 2018 report from the Woodstock Institute claims Chicago's ticketing system disproportionately affects low-income and minority residents.[1] An article from ProPublica in February of the same year entitled *How Chicago Ticket Debt Sends Black Motorists into Bankruptcy* found evidence that Black Chicago motorists are more likely to experience aggressive practices like same-day and consecutive-day ticketing and bankruptcy as a result of unpaid parking tickets.[2] The article led to the November 2018 dismissal of over 23,000 duplicate tickets issued since 1992.[3] Finally, in April of 2021 the Chicago Metropolitan Agency for Planning released a report entitled *Improving Equity in Transportation Fees, Fines, and Fares Findings and Recommendations for Northeastern Illinois* in which researchers found that low-income residents bear the brunt of the cost to maintain public infrastructure services like roads, bridges, and interstates as a proportion of their total income.[4] It would seem that for a city

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[1] "The Debt Spiral: How Chicago's Vehicle Ticketing Practices Unfairly Burden Low-Income and Minority Communities." Woodstock Institute, March 17, 2021.

[2] Sanchez, Melissa, and Sandhya Kambhampati. "How Chicago Ticket Debt Sends Black Motorists into Bankruptcy." ProPublica, February 27, 2018.

[3] "Chicago Throws out 23,000 Duplicate Tickets Issued since 1992 to Motorists Who Didn't Have Vehicle Stickers." National Motorists Association. November 30, 2018.

[4] CMAP. "Equity in Transportation Fees, Fines, and Fares in ..." Chicago Metropolitan Agency for Planning.

with one of the largest wealth gaps in America the transportation system has been a hindrance to equitable and sustainable growth.[5]

1.1 Chicago Wheel Tax

As the most costly and insular of parking policies, the Chicago wheel tax program, which is commonly referred to as the Chicago City Sticker Program, is frequently criticized for its relatively high cost and disproportionate impact on poorer Chicago residents. The City Sticker Program requires Chicago residents to pay an additional vehicle registration fee for a one year "wheel tax vehicle license " which funds "the repair and maintenance of more than 4,000 miles of Chicago streets."[6] In practice, this license takes the form of a sticker drivers display on the right side of their windshield. The price of a city sticker for a standard sized sedan was around $90 in 2018, but this price can range based on a vehicle's curb weight to up to $460.

From 2008 to 2018 the price of Chicago City Stickers increased from $75 to $90, but the ticketed penalty for not having these stickers increased from $120 to $200. The debate surrounding the 2012 hike from $120 to $200 centered on the need for new avenues for balancing the city's budget and increasing compliance. Former City Clerk Susana Mendoza argued for the change as a way to tackle both these goals by targeting "scofflaws" with higher penalties without creating a greater economic barrier to participation. The same year the hike went into effect the city approved a $1 million emergency budget request for additional private ticketing enforcers from the City's longtime partner Serco in "strategic targeting zones". The ticket hike and strategic enforcement were expected to generate $16 million/year in penalty revenue for the city, but it would only generate $1-2 million over the subsequent 6 years, and

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[5] "Mapping Chicago's Wealth Inequality." Crain's Chicago Business.
[6] "Chicago City Vehicle Sticker FAQs." City Clerk of Chicago.

lead to drivers owing around $275 million collectively for City Sticker tickets to the City by 2017.[7]

1.2 Public Concerns

Throughout Mayor Lori Lightfoot's 2019 Mayoral race she campaigned on promises to end the city's "addiction" to penalty revenue, and the first substantive progress on the issue of transportation inequity in Chicago came two years later in January of 2021. After months of dealmaking between the local City Council, Mayor's Office, and Governor, Mayor Lightfoot announced the first set of reforms to Chicago's ticketing system which included an end to driver's license suspensions over unpaid tickets, decreases to city sticker prices and penalties, changes to make the city's ticket payment plans more affordable, and some modest debt relief.[8] In addition to these changes, in November of 2020 a five-year $1.3 billion infrastructure investment deal was announced with provisions to address deferred maintenance and sustainability issues as well as provide "new neighborhood investments that will enhance community vitality and drive economic development."[9]

Despite assurances from policymakers that these policy changes constitute important steps in ensuring transportation equity, many activist groups question if the policy changes go far enough to address the root causes of ticket debt such as ending contracts with private enforcers. In 2021 Democratic Socialist of America filed a complaint in federal court alleging the 75 year deal the City of Chicago entered into with Chicago Parking Meters (CPM) in 2008 gave the company a monopoly over Chicago's parking meter system in violation of federal antitrust laws.

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[7] Wbez. "Chicago Hoped to Generate Millions with Expensive City Sticker Tickets. It Didn't Work." WBEZ Interactive.
[8] Sanchez, Melissa. "Thousands of Illinois Drivers Would Get Their Licenses Back under a Criminal Justice Reform Bill." ProPublica.
[9] City of Chicago. "Mayor Lightfoot Announces Five-Year Capital Plan for Chicago." Chicago.gov.

The complaint alleges CPM was able to fully recuperate $500 million more than their $1.2 billion initial investment by 2019 with over 60 years remaining on the contract. This massive return on investment has not come without cost to Chicago drivers who have faced a quadrupling of parking rates over the last decade as well.[10] The complaint was dismissed in early 2022 based on the doctrine of state action antitrust immunity, but its existence still functions as an important marker for public dissatisfaction with the deal.

CPM is not the only private enforcer that activists have expressed concerns about. In 2006 the City of Chicago entered into a contract with a private staffing agency based in New Jersey named Serco to supplement its ticketing services in certain community areas. Unlike CPM attendants, who are only given ticketing authority for expired meter violations, Serco private enforcers are authorized to enforce almost all municipal and state vehicle violations.[11] Serco operates mainly in Chicago’s most affluent community areas (i.e., Loop, River North, Wicker Park, etc.) during evening and overnight periods. This pattern of behavior has led some to accuse the City of Chicago of “...spreading pain and misery to fellow Chicagoans.” by contracting with the company.[12]

Whatsmore, activists have also complained that the Chicago Police Department has engaged in inequitable ticketing practices like issuing duplicate tickets to meet quotas and boost city revenue. Activists point to a 2 year increase in CPD issued tickets from 2012 to 2014 during a period of low ticketing by other units as evidence of the overly aggressive stance on ticketing by the CPD.[13] Fortunately, in 2014 Governor Pat Quinn signed legislation that banned the use of ticketing quotas by Illinois Police Departments. Despite being an important step towards

[10] Byrnes, Dave. “Federal Judge Dismisses Antitrust Suit Over Chicago Parking Meters.” Courthousenews.com. Courthouse News Service.
[11]Speilman, Fran. “Technology Driven Crackdown on Illegal Parking in the Works.” PressReader.com - Digital Newspaper & Magazine subscriptions.
[12] Better Government Association. “Chicago's Parking Meter Deal a Lesson in 'Worst Practices'.” BGA
[13] Brockway, Mike. “More Parking Tickets Issued in 2013 with More Officers on the Street.” DNAinfo Chicago

unburdening drivers, this act was interpreted by many as confirmation of the prior utilization of socially inequitable ticketing practices in Chicago.[14]

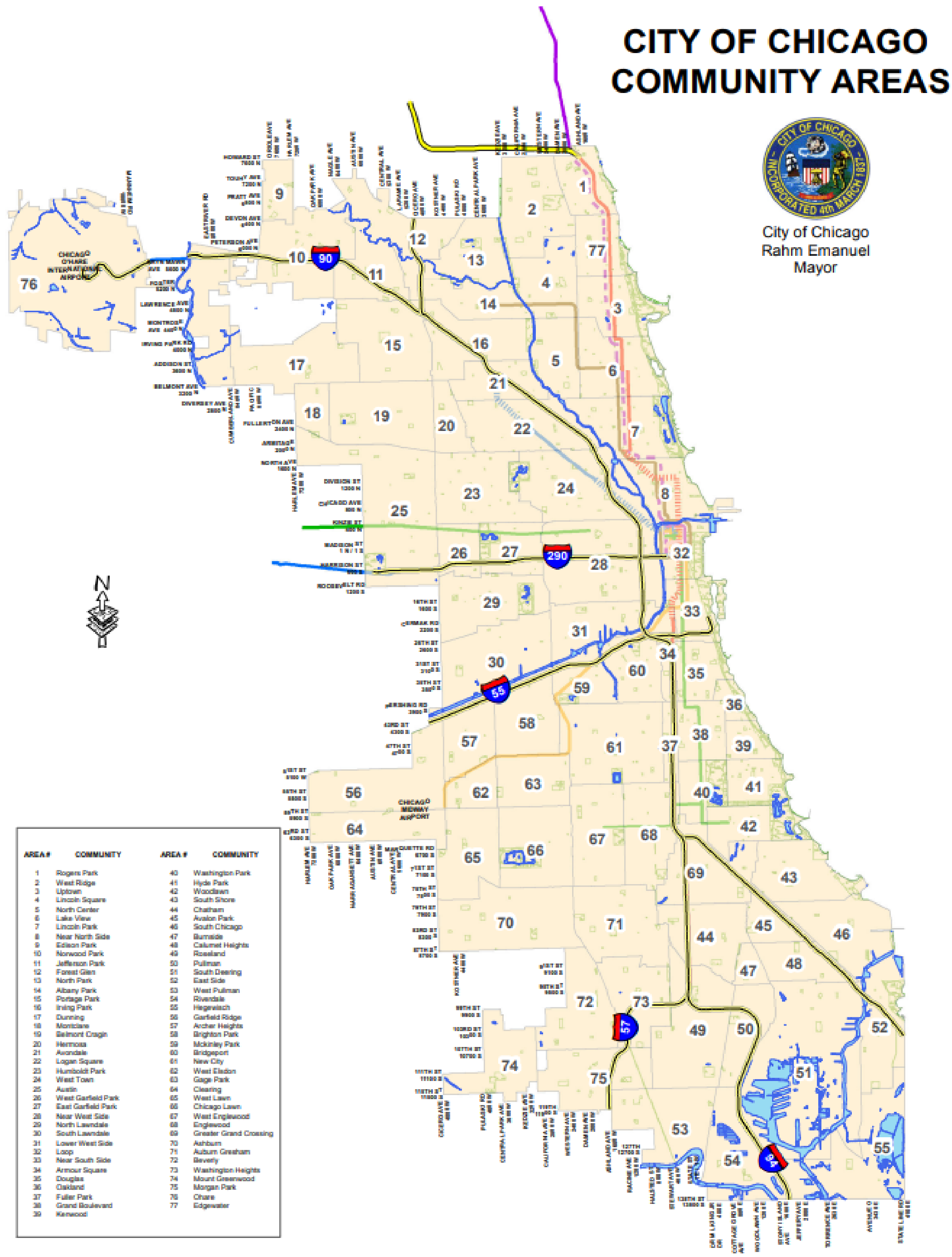
Figure 1.1 (*below*) provides a map of the community area zones during the period of the study and their access to public transit. Figures 1.2-1.4 (*see appendix*) present additional maps which provide several other representations of transportation inequity in Chicago over the last decade from Mayor Lori Lightfoot's Strategic Plan for Transportation 2021. Overall these figures present a picture of a sizable amount of transportation inequity in Chicago. Large parts of the mostly black west southwest and southeastern parts of the city experience relatively higher transportation cost, longer commute times, and less access to the public transit system. These are several of the key metrics this paper concerns itself with in accessing transportation equity in Chicago.

I will now pause to define several key terms in the context of this study before proceeding. Aggressive ticketing in the context of this study is described as ticketing practices regarding parking and vehicle compliance with an economic incentive beyond coercing vehicle owners into compliance with local policy. Examples of aggressive ticketing may include quota systems and sameday ticketing, but this study focuses specifically on the use of third-party enforcers in strategic targeting zones to increase penalties issued. A community area is defined in this context as one 77 well-defined (i.e., non-fluid or overlapping) boundaries in Chicago. These community areas are made up of over 200 smaller neighborhoods, but policymaking and recordkeeping are often done officially with references to these boundaries. Unlike wards, which change with census cycles, and neighborhoods, which can vary very fluidly, these boundaries have not shifted since they were proposed in 1920 by University of Chicago demographers as a way to better track socioeconomic data. Finally, Transportation equity is a way to frame

[14] Smith, Mitch. "New Law Bans Police Use of Ticket Quotas." chicagotribune.com. Chicago Tribune, May 21, 2019

distributive justice concerns in relation to how social, economic, and government institutions shape the distribution of transportation *benefits and burdens* in society.

Figure 1.1: Chicago Community Areas and Primary Transportation Systems (2010)



1.3 Context of Study

This study evaluates transportation equity through the lens of City Sticker ticketing practices to evaluate whether or not private enforcers for Serco acted in an overly aggressive manner relative to other third-party enforcers in the City. Specifically, this study examines ticketing practices around the 2012 policy change and compares the outcome of additional penalties incurred by drivers based on the different enforcement units issuing tickets. The community area is used as the primary level of analysis due to the availability and reliability of socioeconomic data.

The study begins by assuming the following as the null hypothesis: if the 2012 policy changes were intended to increase penalty revenue by targeting scofflaws, there should be no evidence of increased additional penalties generated by either unit when controlling for transportation equity measurements. An increase in penalties in areas serviced by private enforcers when controlling for these metrics would imply the application of aggressive and/ or inequitable approaches designed to maximize penalty revenue beyond those measures outlined in the policy change.

The remainder of the paper is outlined as follows: Section 2 is a literature review that examines the academic literature regarding distributive justice, transportation equity, and Chicago Ticketing Practices. Section 3 describes the research methodology employed. Section 4 then turns to an analysis of ticketing data. Finally, Section 5 provides policy recommendations based on the key findings and briefly concludes the paper.

2. Literature Review

2.1 Overview

The key areas of literature relevant to this study pertain to distributive justice, economic mobility, and transportation equity. The literature surrounding these areas is well developed and varied. Economic mobility has traditionally been evaluated from a philosophical basis of distributive justice with economic arguments layered on top of these philosophical principles. This approach has been able to produce several economic frameworks capable of producing quantitative evidence to support policymaking. As the basis for the philosophical principles can vary, this has led to a wide variety of analytical methods. Similarly, in the current literature on transportation equity there is no standard approach to analyzing transportation equity, however, most of the existing methods of analysis can be generalized into two broad categories: horizontal and vertical equity. Horizontal equity is concerned with how the distribution of impacts is shared between groups of similar needs while vertical equity examines how costs are distributed among different classes.

The next section begins by highlighting the key theories in distributive justice that underpin arguments for increasing economic mobility. The section then highlights several key theories in economic mobility literature before turning to a discussion of the literature surrounding theories of transportation equity. Finally, the section concludes with a brief overview of several recent studies about transportation equity..

2.2 Key Theories

2.2.1 Distributive Justice

One of the oldest theories of distributive justice comes from John Stuart Mill's 1863 work *Utilitarianism*. Mill argues the goal of distributive policies should be to enable each individual to maximize their utility function. In Mill's utilitarian framework all other injustices could be adequately solved by the balancing of economic forces.[15] Utilitarianism's legacy was highly enduring as it formed the dominant ethical basis for much of 19th and 20th century economic thought. In this context, a utilitarian might care only about the ending revenue produced without considering the distribution of payers.

John Rawls's 1971 *A Theory of Justice* presents one of the first and most well known challenges to the ideals of utilitarianism.. Rawls advocates for an egalitarian theory of distributive justice with two main principles. Primarily, a fair society is one in which resources are distributed equally in a society. Secondly, inequality should only be tolerated in a society so long as the inequality lifts the burden on the least advantaged member of a society - Rawls calls this the difference principle.[16] In the simplest of terms, Rawls advocates for "equality of outcomes." An egalitarian might seek a policy where everyone pays a set portion of their income regardless of the absolute magnitude of that income.

John Roemer's 1998 *Equality of Opportunity* built on Rawls's theory of egalitarianism by accounting for societal constraints. Roemer's theory divides egalitarianism into two different categories with different policy making implications. Essentially, Roemer argues, in addition to equality of outcomes there should also be equality of opportunity, or "luck egalitarianism." It is

[15] Mill, John Stuart. *Utilitarianism*. London, Parker, son, and Bourn, 1863
[16] Rawls, John. *A Theory of Justice*. Cambridge, Massachusetts :The Belknap Press of Harvard University Press, 1971.

not enough that outcomes be evenly distributed amongst a society, they should also be proportional to an individual's (dis)advantage. Importantly, Roemer's argument still allows for the presence of inequality in a society if that inequality is the consequence of an individual's own actions i.e., consequences.[17] A policymaker seeking to ensure an outcome consistent with this idea of distributive justice might produce a policy similar to the 2012 policy change in which the barrier to participation was only slightly increased for affordability as compared to the drastic increase in the penalty of noncompliance.

Amartya Sen's capabilities approach which he first proposed in his 1985 work *Commodities and Capabilities* was a marked shift in the discussion of distributive justice. Sen argues questions of what an individual hopes to achieve and what an individual and the resources available to achieve that goal are constrained by what an individual can achieve in terms of capabilities.[18] Martha Nussbaum's 2011 work *Creating Capabilities: The Human Development Approach* builds on Sen's work by identifying those cognisant and noncogniscant capabilities that enable individuals to best achieve their goals. Nussabaum's approach is highly critical of traditional utilitarian and egalitarian theories as she argues these theories breakdown in the face of regional and personal differences in not only access to key resources, but also the ability to translate those resources into economic outcomes.[19] A policymaker seeking to institute a policy consistent with the capabilities approach might extend the registration period for a new City Sticker for members of vulnerable populations.

The final relevant theory of distributive justice comes from David Boaz's 1998 *Libertarianism: A Primer* in which he argues for political liberalism, or the removal of

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[17] Roemer, John E.. *Equality of Opportunity.* Cambridge, MA and London, England: Harvard University Press, 2021
[18] Sen A. Commodities and Capabilities. Amsterdam: North-Holland; 1985.
[19] Nussbaum, Martha C. "Creating Capabilities: The Human Development Approach." Google Books. Harvard University Press.

governmental constraints to personal freedom, as the only appropriate form of distributive justice. Although many of the liberterian principles that Boaz endorses are similar to John Stuart Mill's utilitarianism, Boaz argues preserving an individual's right to self-determination can be more important than the utility another individual receives from redistribution and other regulatory policies.[20] Libertarianism is often excluded from discussions of distributive justice because of its poor policy making implications, but I have included it here for completeness.

These ideas of distributive justice so far mentioned form the bedrock on which theories of economic mobility and transportation equity are built on.

2.2.2 Economic Mobility

Relevant theories of economic mobility can be broadly organized around three main categories of study: the inheritance of inequality through wealth transmission, the genetic transfer of family human capital, and the impact of neighborhood effects and other types of segregation. While the first two categories deal specifically with intergenerational mobility (i.e., the correlation between the economic statuses of parents and offspring), the last category is primarily concerned with intragenerational mobility (i.e., the ability of an individual to improve or to worsen their economic status in their lifetime).

In his 1997 work *The Economics of Inequality* Thomas Piketty lays the groundwork for the study of generationally transmitted inequality. Piketty notes inequality has been on the rise since 1975 globally and suggests inequality of wages and poor redistribution policies are the primary catalysts for this change. Piketty concedes that increasing educational attainment can be an important factor in decreasing inequality though the extent of this increase is constrained by

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[20] David Boaz. "Libertarianism: A Primer." Constitutional Political Economy. Springer

wage inequality and the ideas of distributive justice that dominate the policymaking setting.[21] Bowles et al expand on Piketty's argument in their 2002 work "The Inheritance of Inequality". Bowles et al quantify the differential impacts of sources of persistence of intergenerational earnings by decomposing the correlation coefficient of intergenerational earnings into additvive parts. Bowles et al conclude cultural factors, genetics, and inheritances are the main avenues for the intergenerational transmission of income. Though the authors admit the presence of cultural and genetic factors have an additive effect on the correlation of parent and offspring income, Bowles et al conclude parental wealth and ability to be the most important factor in predicting intergenerational income mobility. [22]

In contrast to the previously mentioned authors who attribute rising inequality to intergenerational transmission of wealth and ability, Heckman et al propose a theory of intergenerational mobility primarily concerned with the transmission of cognitive and noncognitive skills through social channels in their 2014 work The Economics of Human Development. Heckmen et al propose a model of earnings that is dependent on the additive vector of skills and health stocks. The maximization of this vector of skills is the most important determinant of lifelong earnings. According to their model of skills formation, investments in education and the development of noncognitive social skills provide the greatest return on investment in terms of decreasing inequality between social groups.[23] Relatedly, Steven Durlauf emphasizes the importance of neighborhood effects on income mobility in his 1996 work "Neighborhood Feedbacks, Endogenous Stratification and Income Inequality." According to Durlauf policies like segregation constrain the economic outcomes perceived possible, which

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[21] Piketty, Thomas. (2015) 2015. *The Economics of Inequality*. 15th edition. Harvard University Press.
[22] Bowles, S. and H. Gintis. 2002. "The Inheritance of Inequality." Journal of Economic Perspectives 16: 3-30.
[23] Heckman, J. and S. Mosso. 2014. "The Economics of Human Development and Social Mobility." Annual Review of Economics 6: 689-733.

limits the production function of offspring. Durlauf points to significant correlation between parental and offspring incomes across neighborhoods and increases in income mobility with geographical relocation as further evidence of the importance of factors outside of the transmission of ability and wealth.[24] Inequitably distributed ticketing can function as a societal constraint as Paul Kiel and Hannah Fresques show in their 2017 work *Bankruptcy and Race in America*. Kiel and Fresques use a multivariate logistic regression to link rising bankruptcy rates in black communities from 2012 to 2016 to increasing outstanding ticket debt when controlling for other characteristics.[25] In these neighborhoods, aggressive enforcement can form a type of "ceiling" that makes it too expensive to transition to the next income level and perpetuates inequality.

2.2.3 Transportation Equity

Unlike theories of distributive justice and economic mobility that have been discussed at length by academics, the recent study of transportation equity has mainly been led by nongovernmental organizations and policymakers. Broadly grouped these studies focus on horizontal and vertical equity. Though they are measured in slightly different ways, the Federal Transit Administration emphasizes a focus on strengthening both of these objectives on their transportation equity planning topics website.[26]

Todd Litman explicitly describes ideologies of equitable transportation in these two broad categories in his 2014 work *Evaluating Transportation Equity Guidance For Incorporating Distributional Impacts in Transportation Planning.* According to Litman, a focus on horizontal

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[24] Durlauf, S. 1996. "Neighborhood Feedbacks, Endogenous Stratification, and Income Inequality." Dynamic Disequilibrium Modeling, ed. W. Barnett, G. Gandolfo, and C. Hillinger, Cambridge: Cambridge University Press.

[25] Fresques, Paul Kiel and Hannah. "Data Analysis: Bankruptcy and Race in America." ProPublica

[26] The Transportation Planning Capacity Building Program. "Planning Topics." Collaboration - Transportation Planning Capacity Building Program

equity treats all groups equally and seeks to impose the cost of access equally on each individual. In contrast, vertical equity tends to be more progressive with respect to incomes, benefits to disadvantaged groups, and improvements in basic access. Littman presents six impact categories for analyzing transportation equity: public facilities and services, user cost and benefits, service quality, external impacts, economic impacts, and regulation and enforcement - the focus of this study.[27] Instead of providing one concrete policy reform to increase equity, Littman concludes his work by calling for policymakers to rely on socioeconomic data of their constituents to decide on horizontal or vertical approaches to transportation equity given resource constraints.[28]

In their 2016 work "Public Transit Equity Analysis at Metropolitan and Local Scales: A Focus on Nine Large Cities in the US" Griffin et al present findings from one of the largest transportation equity studies ever created. Griffin et al take a vertical approach by choosing to ignore issues of accessibility based on race and instead focus on income classes. Griffin et al use data from the EPA's Access to Jobs and Workers via Transit database combined with variables for communities like annual vehicle miles traveled, park access, and proximity to transit to perform both a descriptive and spatial analysis of levels of access enjoyed by different income groups in nine large cities. The authors conclude more equitable cities coordinate accessibility efforts with other social engineering goals such as affordable housing and efficient land usage.[29] Chicago was not included in the study, but the findings are still relevant given the national representation of the dataset.

Yehaneh et al investigate horizontal equity when they pick up the issue of race based transportation inequity in their 2018 work "A Social Equity Analysis of the US Public

[27] I.b.i.d. 14
[28] Litman, Todd. "Evaluating Transportation Equity." Victoria Transport Policy Institute. Victoria Transport Policy Institute, April 21, 2021.
[29] Griffin, Greg P & Sener, Ipek N. 2016. Public Transit Equity Analysis at Metropolitan and Local Scales: A Focus on Nine Large Cities in the US. Journal of Public Transportation, 19 (4): 126-143.

Transportation System Based on Job Accessibility." Yaheneh et al use data on population job accessibility from the Center for Transportation Studies at the University of Minnesota, 5 year census data, and equity indicators like the GINI Index in a linear regression model to create a justice scale based on the outcomes of different racial groups. The researchers find minorities and low income individuals have the highest job accessibility with differences in income levels mattering more than racial differences in smaller metropolitan areas. There is an increasing tilt towards racial differences as metropolitan size grows or income levels decrease.[30] The second part of this statement is most relevant as Chicago is the nation's third largest city and has a high low-income minority population. Like Griffin et al, Yaheneh et al use a national dataset that allows for the creation of general trends, but, as previously mentioned, Chicago is an expected exception to their findings. Importantly, this study most closely resembles the method detailed in Section III.

2.2.4 Chicago Transportation Equity

The most relevant study in transportation equity comes from an April 2021 report by the Chicago Metropolitan Agency for Planning (CMAP) entitled *Improving Equity in Transportation Fees, Fines, and Fares Findings and recommendations for Northeastern Illinois* which analyzed equity in the northeastern Illinois transportation system with a focus on Chicago. CMAP employs a vertical equity approach and regression analysis of transportation spending relative to usage variables like annual vehicle miles traveled in their analysis. CMAP researchers found that low-income residents bear the brunt of the cost to maintain public infrastructure services like roads, bridges, and interstates as a proportion of their total income while simultaneously using

[30] Jeddi Yeganeh, Armin, Ralph Hall, Annie Pearce, and Steve Hankey. 2018. "A Social Equity Analysis of the U.S. Public Transportation System Based on Job Accessibility". Journal of Transport and Land Use 11 (1).

less of these resources as well. Decades of underfunding and overreliance on income from penalties are cited as the main causes of this inequity. CMAP researchers conclude a decrease in transportation user fees is necessary to combat undue burdens on low income residents.[31]

2.3 Relevancy to the Literature

The authors presented above are by no means intended to constitute a holistic review of all relevant literature related to the topics concerned. Instead, I have chosen to highlight the most relevant theories and studies for the analysis of the transportation equity in Chicago with regards to ticketing practices and their effects.

By focusing on the community areas within one city. This study applies theories of distributive justice to the analysis of punitive fee systems in the context of transportation equity specifically in Chicago. Similarly, this study contributes to the economic mobility literature by expanding the subject of analysis beyond wealth metrics to the effect of punitive measures like ticketing on economic outcomes.

Finally, the literature regarding Chicago parking tickets is less robust than the attractive headlines may seem. Aside from the ProPublica *Ticket Trap* the ticketing data has only been cited a few times in academic settings, most notably by Ryan Kessler in his 2020 PhD. dissertation. Kessler performs a difference-in-difference analysis to explore the relationship between fines and bankruptcy at the individual level. I apply a similar approach for the same time period, but analyze the enforcing agent to explore how differences in implementation between community areas relates to outcomes.

[31]CMAP. "Equity in Transportation Fees, Fines, and Fares in ..." Chicago Metropolitan Agency for Planning.

3. Methods:

I use a difference-in-differences approach to evaluate differences in implementation of the 2012 policy change at the community area level. I combine publicly available ticketing data from ProPublica's *Ticket Trap* with transport equity indicators from CMAP to create a linear model of ticketing outcomes based on community area characteristics.[32] The remainder of the section is organized as follows: section 3.1 gives an overview of the data and key variables obtained from each source. section 3.2 explains the key concepts of the difference-in-difference approach and justifies this approach in this study. Finally in section 3.3 I explain the filtering process for creating control and experiment groups and provide a brief analysis of ticketing trends in defense of the model assumptions.

3.1 Data Sources

3.1.1 ProPublica Ticket Data Set

The City of Chicago began collecting ticketing data for public disclosure in 1998. Each ticket issued in Chicago since then is required to list the issue date, enforcing unit, community area, zip code of the vehicle's registration, violation code, and other identifying information. Table 3.1 contains a list of all the variables included in the ProPublica ticketing data set. This data contains information for over 20 million tickets issued from 1998 until 2018. I used Microsoft Excel's SQL Power Query in order to filter the data to relevant years and ticket types. This left me with a dataset of 911,744 observations of tickets issued between 2009 and 2014.

I create the outcome variable from the ProPublica ticketing data using as well. As the policy change applies to tickets for expired City Stickers, the key outcome of interest to this

[32]WBEZ, ProPublica &. "City of Chicago Parking and Camera Ticket Data." ProPublica Data Store. ProPublica, May 2018. https://www.propublica.org/datastore/dataset/chicago-parking-ticket-data.

study is the amount of ticketing penalties incurred above the original penalty amount when issued. Specifically, this amount takes the form of the original fine amount subtracted from total payments and current amount due to produce total penalties above the original fine.

$$\textit{Total Penalties}_{Net} = (\textit{Current Amount Due} + \textit{Total Payments} - \textit{Original Fine Amount}) \quad \textbf{eq.1}$$

This value was then converted to a percentage by dividing by the original fine amount before being scaled around the average for each community area in each month. This was done to allow me to compare across periods with different original fine amounts (i.e., before and after the 2012 change), between community areas with different ticketing rates, and to control for the fact that every observation initially ticketed some original fine amount.

Since this study seeks to explore the enforcement decisions both before and after the policy change, defining total penalties in this way enables the comparison of enforcement decisions that were more likely to increase penalty revenue beyond simple compliance issuance. Essentially this is a good faith argument meant to remain consistent with the null hypothesis. The City of Chicago has a right to increase compliance with the wheel tax policy, but, if the doubled penalty led to an increase in the net total penalties incurred by drivers when controlling for the amount of the fines, community areas, and total tickets issued per community area, this would suggests implementation was aggressively implemented to increase the amount of additional late fees incurred by drivers, specifically in areas with third-party enforcers. Table 1 contains a list of the key variables obtained from the ProPublica dataset and their definitions. There were well over 100,000 observations included in the regression from this dataset.

Table 3.1: Key Variable from the Propublica Ticket Data Set

Key Variables from the ProPublica Ticket Data Set		
Variable	**Description**	**Other Relevant Information**
Ticket Number	Unique ID for each citation	Contains an indicator for same day tickets that were issued. These made up less than .05% of City Sticker Tickets issued over the time period
Issue Date	Date and time the ticket was issued	Day, Month, Year, and Hour variables were created from this date-time
Unit	This number relates to subcategories within units, such as police precincts or private contractors	A Table of the Top 10 units and their descriptions is included in section 3.3.2 This variable was used to create an indicator for the neighborhood enforcer type
Fine Level 1 Amount	Original cost of citation	*This variable was scaled to make comparisons across time periods and vehicle types possible.*
Fine Level 2 Amount	Price of citation plus any late penalties or collections fees.	Unpaid tickets can double in price and accrue a 22-percent collection charge.
Current Amount Due	Total amount due for that citation and any related late penalties	As of May 14, 2018, when data was last updated
Total Payments	Total amount paid for ticket and associated penalties	As of May 14, 2018, when data was last updated.
Community Area Number	The numeric code associated with the Chicago community area that the geocoded point falls in	See Figure 1.1 for a map of Chicago with community area names and numbers
Community Area Name	The name of the Chicago community area that the geocoded point falls in	

3.1.2 CMAP Community Profiles

The Chicago Metropolitan Agency for Planning releases regular Community Data Snapshots (CDS) reports of socioeconomic indicators aggregated for Chicago's community areas over four year periods. The 2015 CDS report covers the period from 2009 until 2013 and is the primary report used to assign socioeconomic indicators to the ProPublica ticketing observations based on community area.[33] The CDS reports also aggregate this data at the municipal and county level, but this level of aggregation is obviously uninformative when looking at differences in ticketing practices between community areas. All indicators were scaled around the mean for all community areas during the time period to better enable comparisons of the impact of changes in the indicator and ticketing outcomes. Despite the difference in the range of the studies, the 2009 to 2013 CDS was chosen as a reference due to its best fit with the period of the study given the division of statistics into four year periods. Table 2 (below) provides a brief list of the variables selected from the data with descriptions.

Table 3.2: Key Variables from the 2009 - 2013 CMAP Community Data Snapshot

Key Variables from the 2009-2013 CMAP Community Data Snapshot		
Variable	**Description**	**Measurement Source**
Annual Vehicle Miles **	Average Vehicle Miles Traveled Per Resident	CMAP analysis of US Census Bureau Data & Illinois Environmental Protection Agency Odometer readings
Transit Ridership **	Number of Residents using Public Transit to go to Work (%)	2009-2013 American Community Survey

[33] Chicago Metropolitan Agency for Planning. "Community Data Snapshots Raw Data, July 2021 Release with 2020 Supplement - Archive: August 2015 Cds Raw Tables." CMAP Data Hub. CMAP, March 2014. https://datahub.cmap.illinois.gov/dataset/community-data-snapshots-raw-data/resource/1daedd0e-b662-4f60-9dc8-71c65c8b51bb.

Variable	Description	Measurement Source
Total Commuters **	Total number of Resident who Commute for Work in an Area	2009-2013 American Community Survey
Residents who Work at Home **	Number of Residents not Commuting for work	2009-2013 American Community Survey
Asian Population *	Asian Population (%)	2009-2013 American Community Survey
Black Population*	Black Population (%)	2009-2013 American Community Survey
Hispanic Population*	Hispanic Population (%)	2009-2013 American Community Survey
White Population*	White Population (%)	2009-2013 American Community Survey
Median Income**	Median Income of Community Area Residents	2009-2013 American Community Survey

**** Correspond to Measures of Horizontal Equity***
***** Correspond to Measures of Vertical Equity***

3.2 Difference-in-Difference Model

I estimate total penalties as described in **eq.1** by community area using a linear difference-in-difference regression in which common transportations equity indicators serve as controls. This regression was run for different time periods as well as with different combinations of indicators to confirm the robustness of the findings. The different regressions are detailed further in Section 4. The remainder of this section explains the difference-in-difference approach, its limitations, and justification for employing the approach in the context of this study.

3.2.1 Concept

Differences-in-difference strategies are simple panel models applied to sets of group means to estimate the differential effect of exposure to an intervention or policy change between an experiment and control group. The basic concept behind the difference-in-difference approach is that by comparing the differences between the experiment and control groups before and after the policy change one can make plausible determinations of the effect of the policy on the different groups. Importantly, this approach allows for experimental analysis of groups that might be more difficult to track on the individual level as long as the group trend was consistent over time. Labor economists were the first to employ the difference-in-difference approach to topics like job training in the 1970s, but their use has varied between industries and policy topics since then.[34]

The intuition behind the difference-in-difference approach takes the following form:

$$(Treatment_{post} - Treatment_{pre}) - (Control_{post} - Control_{pre}) = Diff\text{-}in\text{-}Diff\ estimate \quad \textbf{eq.2}$$

The average of the treatment group before the effect is subtracted from its average after the effect. The same is done with the control group. These averages are then subtracted from each other to produce the difference-in-difference estimator. If this estimator is greater than 0 with significance then this implies the presence of the treatment had an effect on outcomes.

The basic statistical model of the difference in difference approach takes the following form:

[34] The Economics of Education . “Difference-in-Differences.” Difference-In-Differences - an overview | ScienceDirect Topics.

$$Y = \beta_0 + \beta_1 * [Treatment] + \beta_2 * [Intervention] + \beta_3 * [Treatment * Intervention] + \varepsilon \quad \textbf{eq.3}$$

Y is the predicted estimate of our outcome variable (i.e., total penalties). Here ***Y*** would refer to the average distance in the mean tickets in each neighborhood. $\boldsymbol{\beta_0}$ refers to the intercept, which is the average penalty of the control group before the policy change. This can be thought of as the baseline average expectation in non-serco contracted community areas. $\boldsymbol{\beta_1}$ is the average difference between groups before the policy change. Treatment is a dummy variable indicating treatment or control group. Here treatment would be serco enforced community areas. $\boldsymbol{\beta_2}$ represents the change in the outcome of the control group after the policy change. Intervention is another dummy variable that represents whether or not the policy was enacted or not. $\boldsymbol{\beta_3}$ represents the difference-in-difference estimator from **eq.2**. This is the key output of interest from the regression because it tells us the impact of the policy change of outcomes given the presence of the treatment (i.e., the private parking enforcer) after the policy enactment.[35] The error term is referred to by $\boldsymbol{\varepsilon}$.

Theoretically speaking, the difference-in-difference approach controls for differences between the experiment and control group if they are almost homogeneous, but one could choose to improve the predictions of this model by adding variables to control for the differences within both groups. A difference-in-difference model using this approach uses a statistical model as follows:

$$Y = \beta_0 + \beta_1 * [Treatment] + \beta_2 * [Intervention] + \beta_3 * [Treatment * Intervention] + \boldsymbol{\delta} X_1 + \ldots + \boldsymbol{\delta} X_1 + \varepsilon \quad \textbf{eq.4}$$ [36]

[35] Torres-Reyna, Oscar. "Differences in Differences (Using R) ." Princeton.edu. Princeton University, August 2015
[36] LA;, Zeldow B;Hatfield. "Confounding and Regression Adjustment in Difference-in-Differences Studies." Health services research. U.S. National Library of Medicine, May 2021.

The model is similar to the model from eq.3 but includes a $\boldsymbol{\delta}$ coefficient representing the effect of variable $\boldsymbol{X_i}$**.** Chicago community areas are not homogenous, so I choose to use an approach similar to **eq.4** to control for common measures of vertical and horizontal equity as described in ***Table 3.2*** both jointly and separately.

3.2.2 Assumptions & Limitations

The primary assumption of concern in the difference-in-difference approach is the assumption of parallel trends between the treatment and control groups. The difference-in-difference approach assumes the differences in outcomes would have followed the same trajectory had the policy intervention not occurred. The interpretation of $\boldsymbol{\beta_3}$ (i.e., estimated policy impact) is relative to the counterfactual that the groups would experience similar trends in a world without the policy intervention. Importantly, $\boldsymbol{\beta_3}$ should not be interpreted solely as the difference between one group versus another, which is contained in the other terms of the model, but as the difference between the outcomes of the groups given the presence of the policy change. I explain the filtering process for the experiment and control groups in the next section before showing the parallel trends assumption holds for these groups in two categories in Section 3.3.3.

3.3 Comparison Groups

Though the outcome of interest is the final ticket amount, the control and experiment groups were primarily selected based on the total tickets issued in the community area and relative composition of ticketing units in comparison to the enforcement patterns across the city.

I began by filtering the community areas based on ticketing frequency before turning to a focus on unit presence. Figure 3.1 shows the most ticketed community areas in chicago. The average for all community areas was around 2,500 tickets issued with a strong upward bias, so community areas with less than 2,500 tickets were excluded from consideration for peer groups considering Serco only operates in areas with at least 3,600 tickets issued per year which can be seen with the neighborhoods marked with an *. This eliminated about 40 community areas. This was done to prevent neighborhoods with non representative total levels of ticketing from misinforming the broader analysis of citywide outcomes. Figures 3.1.1 & 3.1.2 (*see appendix*) feature bar column graphs of this filtering process with the average tickets at each level.

I then filtered these groups based on the enforcement composition in each area relative to the average for the City of Chicago. Table 3.3 (*below*) displays the top ticket issuers on an annual basis. Serco issued over 10% of the tickets over the period while city finance units issued around 46% of total city sticker tickets. The different CPD districts accounted for around 30% of the total tickets issued with only around 3% issued by each unit. Policing enforcement is variable by district and beyond the bounds of this study, but the average enforcement was considered when filtering neighborhoods for the control group. The final neighborhoods selected can be viewed in Figure 3.2 (below). All neighborhoods that are defined as “Serco areas” (red) are areas where Serco issued at least 10% of the total tickets, CPD units issued less than 15% of tickets, and the city units issued less than 50% of total tickets. A greater weight was given to the city units due to their oversized representation in the data set as can be seen in Figures 3.3 & 3.4 (*see appendix*). “City enforcement areas” (blue) were defined as neighborhoods where city units issued at least 46% of all tickets, Serco issued less than 5% of tickets and CPD units issued less than 30% of all tickets.

Figure 3.1 Total Tickets

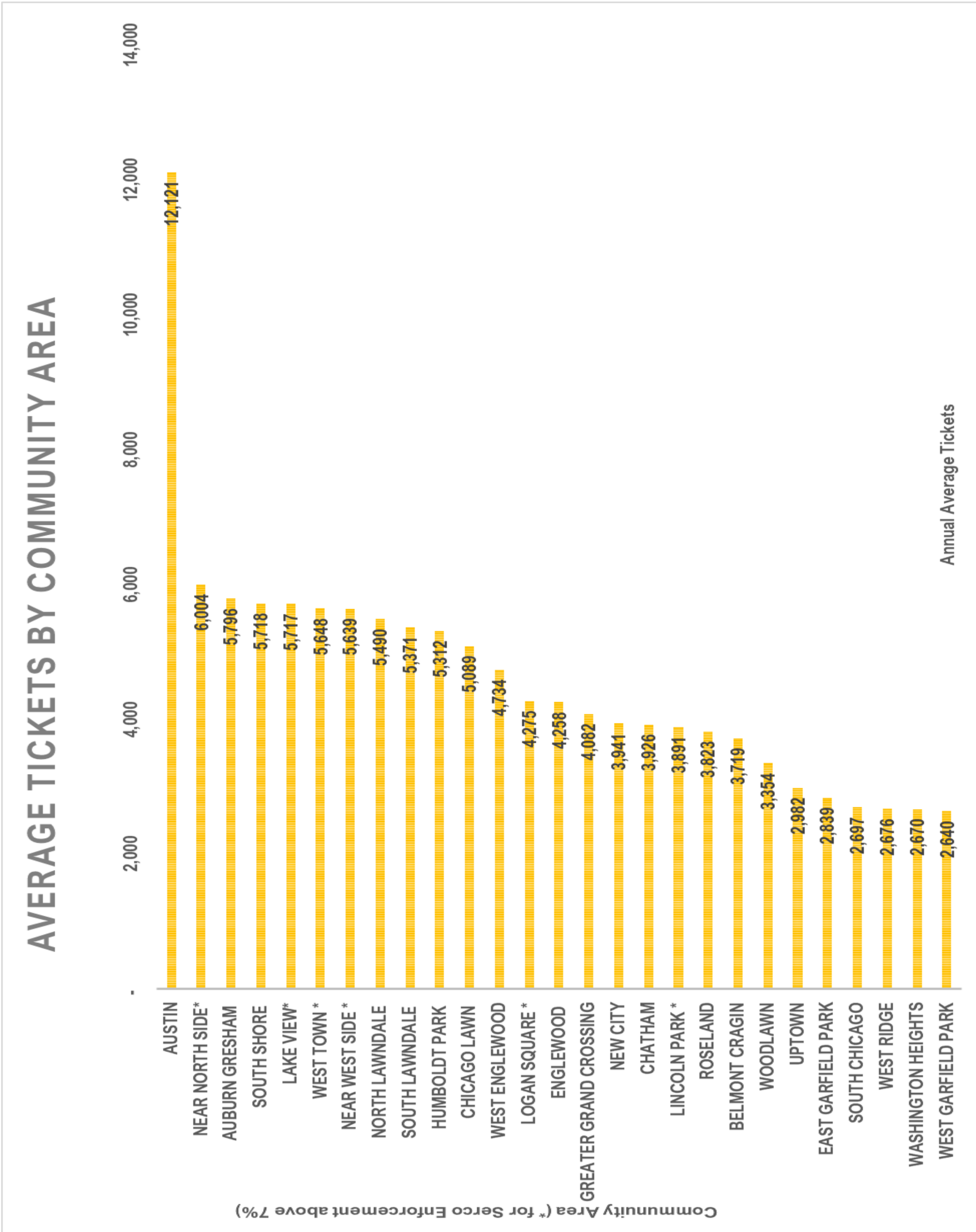
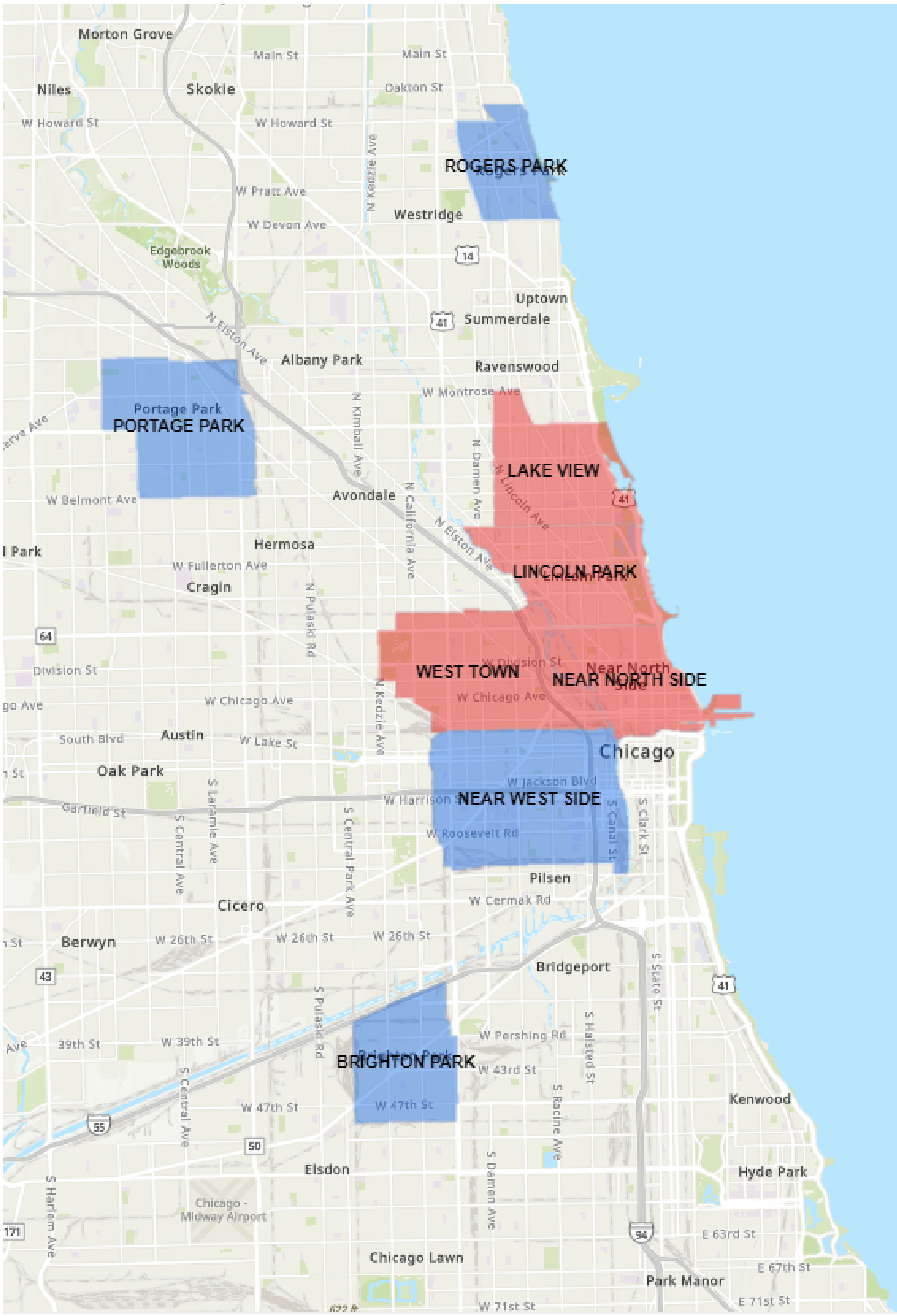


Table 3.3: Top Ticket Issuers

Top Ticketers by Unit				
Unit	**Unit Description**	**Unit Name**	**Average Tickets Issued**	**% of Total of Top Ticketers**
498	DOF	Department of Finance	70206	41%
502	***DOF***	***SERCO***	***12461***	***7%***
501	Miscellaneous	City Clerk Office	9676	5%
15	CPD	5701 W. Madison (Austin)	9345	5%
11	CPD	3151 W. Harrison (East Garfield Park)	7221	4%
7	CPD	6120 S. Racine (Englewood)	7138	4%
10	CPD	3315 W. Ogden (North Lawndale)	6105	4%
4	CPD	2255 E. 103rd Street (South Deering)	5828	3%
6	CPD	7808 S. Halsted (Auburn Gresham)	5780	3%
3	CPD	7040 S. Cottage Grove (Woodlawn)	5774	3%
8	CPD	3420 W 63rd (Chicago Lawn)	5589	3%
2	CPD	5101 S. Wentworth (Fuller Park)	5464	3%
22	CPD	1900 W. Monterey (Morgan Park)	5312	3%
412	CPD-Other	Other Police	5234	3%
25	CPD	5555 W. Grand (Belmont Cragin)	5217	3%
504	***DOF***	***SERCO***	***5054***	***3%***
Total of Top Ticketers			171,404	1

Serco accounts for around 10% of the average tickets in a year.

Figure 3.2: Map of Experiment and Control Group[37]



Source: Generated using ArcGIS & data from the City of Chicago Data Portal

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[37] *Note:* The community areas colored in red refer to the treatment group. These are areas where the private enforcer is present. The community areas colored in blue refer to the control group. These are comparable areas where City of Chicago units were the primary enforcer. See Section 3 for more information on group selection.

3.3.2 Satisfying the Parallel Trends Assumption

Once the control group was established the parallel trends assumption was confirmed for both the tickets issued and the average penalties for both groups. Both groups experience parallel trends in average tickets and tickets per day over the time period. Figures 3.3 & 3.4 (*below*) present the findings from this analysis. There are several important facets to note here. Primarily, although Serco areas saw enforcement levels much higher than city areas in terms of total tickets issued, these tickets did not result in higher penalties on average. Secondly, both graphs have notable inflection points roughly 6 months before the policy change. The aggressive stance on ticketing was announced to go into effect in February of 2012 (solid vertical line), however roughly six months before the official change in August of 2011 (dotted vertical line) there is the greatest difference in outcomes between the two groups. This effect was explored by running the analysis separately for both dates as premature enforcement could be another example of aggressive ticketing.

Figure 3.3 Average Tickets Per Day: Serco Areas v. City Areas

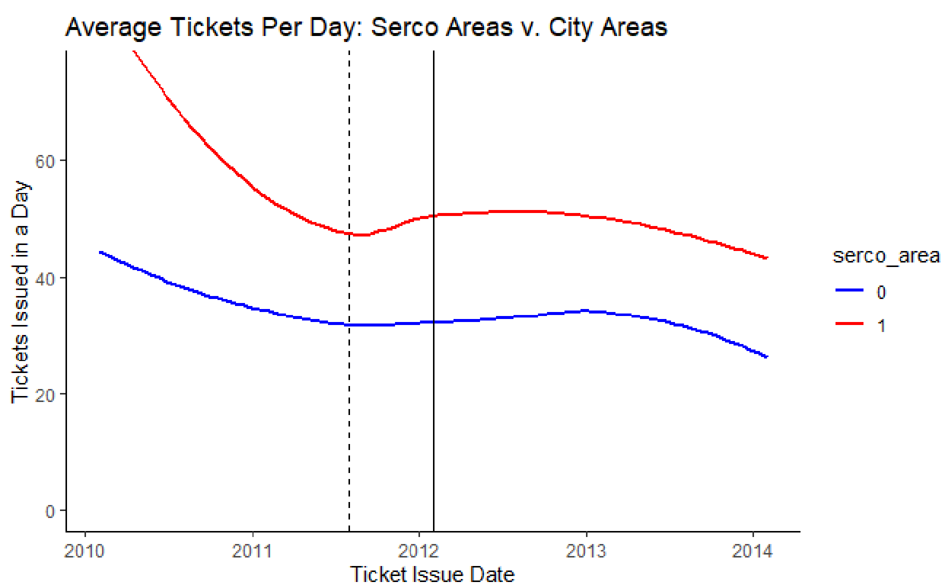
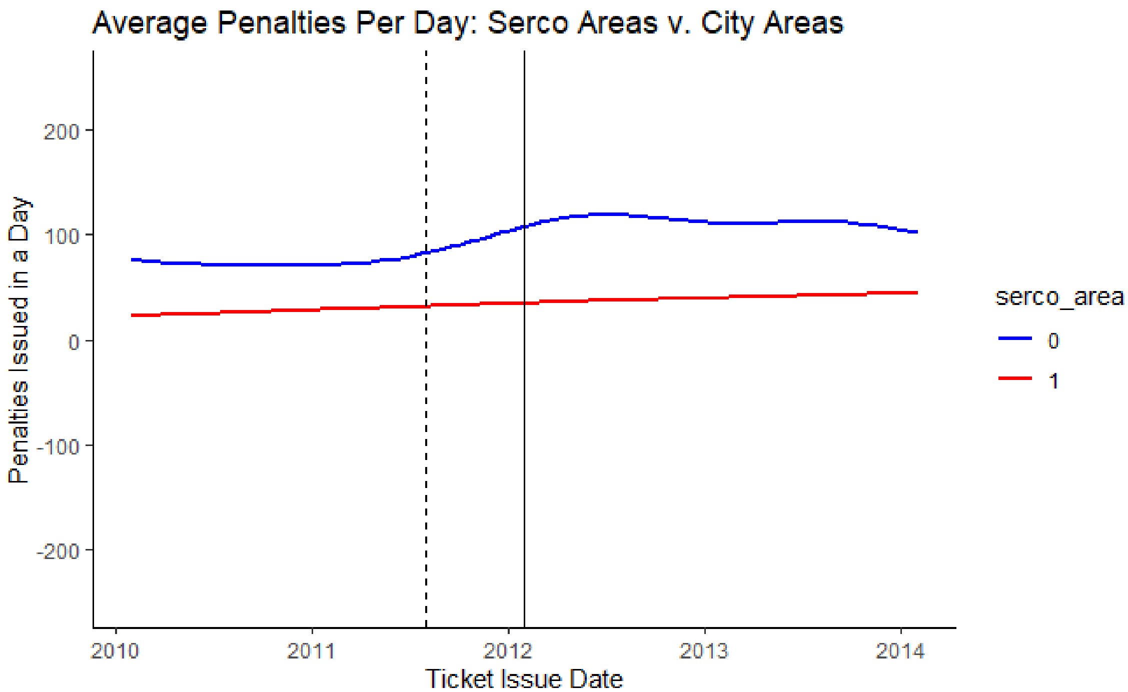


Figure 3.4 Average Penalties Per Issuance Day: Serco v. City Areas



4 . Data Analysis

4.1 Analysis

After applying the difference-in-difference regression in the manner described in Section 3, I find that neighborhoods with Serco enforcement were slightly less likely to issue tickets resulting in more penalties compared to the department of finance when controlling for transportation inequity in between community areas. This finding was consistent for both possible starting enforcement dates. Figures 4.1 (below) display the output of the regression equation. The highlighted coefficient for *did* is the $\boldsymbol{\beta_3}$ term in the statistical model from **eq.4,** which refers to the change in the treatment and control groups given the policy change.

Figure 4.1 Difference-in-Difference Output: Stated Time of Policy Change

```
Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)          0.158780   0.029259   5.427 5.75e-08 ***
serco_enforced1      0.153407   0.041280   3.716 0.000202 ***
policy_enacted1      0.017618   0.009342   1.886 0.059293 .
did                 -0.036053   0.012018  -3.000 0.002701 **
annual_vehicle_miles -0.083709  0.041228  -2.030 0.042317 *
total_commuters      0.129921   0.036277   3.581 0.000342 ***
work_at_home        -0.222499   0.056283  -3.953 7.71e-05 ***
transit             -0.012880   0.001453  -8.865  < 2e-16 ***
white               -0.005740   0.042723  -0.134 0.893124
hisp                 0.038935   0.037580   1.036 0.300176
black                0.121531   0.021903   5.549 2.89e-08 ***
asian               -0.046695   0.025477  -1.833 0.066835 .
med_inc             -0.075094   0.021627  -3.472 0.000516 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The difference-in-difference coefficient should be interpreted as the estimated change in the mean outcomes of Serco community areas and city community areas after the policy change when controlling for transportation equity factors. The regression output in Figure 1 suggests that Serco enforced community areas experienced a decrease in total penalties incurred after the policy change. The extremely low p-value means this finding was statistically significant at the 1% level, which is much lower than the typical 5% level of significance needed to dispel the null hypothesis that the treatment had no effect.

The equity coefficients were also statistically significant at the 5% level with the exception of the percentage of the population that is asian, white and hispanic. The negative coefficients for annual vehicle miles, work from home, public transit riders, and median income all indicate outcomes were inequitably distributed towards the less advantaged community areas. These results are consistent with the findings of Kessler and others. Similarly, the positive estimate for the black coefficient implies communities with more black residents were impacted to a greater extent as result of the policy change. Notably, the results of the study imply the relationship between third-party enforcers and ticketing might go in the opposite direction than many think. Serco enforced areas actually experienced less of a change in ticketing outcomes as result of the policy change than community areas where the City was the primary enforcer.

Of course, this result could be interpreted to conversely mean that the City of Chicago acted more aggressively than the private enforcer during the period after the policy change. This would serve as the most plausible explanation for the difference in outcomes given the incentives of each actor. At the organizational level Serco has little incentive to produce more penalty revenue given the prepaid structure of their contract. Any direction to ticket areas more heavily in an attempt to increase penalty revenue is likely to come from City officials in which case one might expect the City Officials to take a similarly aggressive stance in enforcement.

Additionally, the Serco contract is structured so that Serco is liable for any improperly administered tickets as well as those challenged in court. This provides less of an incentive to issue duplicate tickets as well. The internal practices of Serco are protected by proprietary rights, but former employees have complained of excessive commitment to total ticket numbers. Anecdotes like these lead me to believe the first possibility is a much more likely explanation of the findings.

The regression was also run with the policy enacted date as 6 months prior to the 2012 official enactment date. Similar estimates were obtained. Results for that regression can be found in *Figure 4.2* (*below*). The regression was also run at different intervals around the policy change. The results of that study, as well as, all the R code used to create the study can be found in Appendix 2. Notably, the findings were much more robust for different time intervals when the 2011 enactment date than with the stated date of the policy change. This would support the theory that aggressive ticketing practices were instituted prior to the official policy change.

Figure 4.2 Difference-in-Difference: Inflection Point of Total Tickets (6 Months Before)

```
Coefficients:
                     Estimate Std. Error t value Pr(>|t|)    
(Intercept)          0.178641   0.032209   5.546 2.93e-08 ***
serco_enforced1      0.214768   0.045189   4.753 2.01e-06 ***
policy_enacted1      0.012990   0.009779   1.328  0.18404    
did                 -0.035324   0.012555  -2.814  0.00490 ** 
annual_vehicle_miles -0.180980  0.058001  -3.120  0.00181 ** 
total_commuters      0.206651   0.049329   4.189 2.80e-05 ***
work_at_home        -0.359351   0.078651  -4.569 4.91e-06 ***
transit             -0.015676   0.001844  -8.501  < 2e-16 ***
white               -0.028370   0.048380  -0.586  0.55760    
hisp                 0.070823   0.038541   1.838  0.06612 .  
black                0.162139   0.024609   6.589 4.46e-11 ***
asian               -0.098503   0.035030  -2.812  0.00492 ** 
med_inc             -0.043561   0.027312  -1.595  0.11073    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

4.2 Limitations

I would now like to pause to caution the reader against the overzealous interpretation of the results previously outlined. Firstly, the study intentionally contains itself to an analysis of a specific municipal code violation during a specific time around the policy change. This was done with the belief that this was the best way to generate the most accurate measurements of the impact of a policy change during that period with economic benefits directly linked to the City of Chicago. While these findings are not appropriate for overly broad statements on transportation equity based on the individual outcomes, they do indicate the inequitable implementation of the 2012 price hike from an enforcement standpoint at the community level. This study could be built on by exploring the policy impact at the individual level, but that may be impossible at the current moment due to privacy concerns.

5. Policy Recommendation and Conclusion

5.1 Increased Serco Enforcement

The 2011 annual Budget Options for the City of Chicago report produced by the City's Office of the Inspector General estimated that the City of Chicago could save an estimated $1.1 million per year by switching to Serco as the exclusive ticketing enforcer in the City.[38] Meanwhile, the 2012 hike in City Sticker prices generated less than $2 million after six years.[39] Giving more ticketing authorities to Serco could have generated almost $8 million in savings over the same period from the reduced labor costs alone. Additionally, assuming that the trend between the control and treatment groups described in Section 4.1 holds for other Chicago Community Areas, ticketing outcomes would be less inequitably distributed than under mostly City enforcement. Furthermore, had the savings from the Serco contract been directed towards lower City Sticker Costs this could lower the barrier to entry for non compliant drivers, and, hopefully, increase long term revenue.

5.2 Conclusion

In this study I have analyzed differences in ticketing outcomes between enforcement units in the 4 years around the 2012 City Sticker hike. I find that the presence of the private enforcer led to less penalty revenue collected by the City above the initial penalty amount, which is consistent with the belief that the policy change led to inequitable ticketing outcomes. By exploring ticketing outcomes for each unit while controlling for transportation inequity between community areas, I contribute findings to the literature on transportation (in)equity in Chicago.

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[38] IGO, "IGO- Savings and Revenue Options 2012- Final- September ..." chicagoinspectorgeneral.org. Office of the Inspector General - City of Chicago, September 2011

[39] Wbez. "Chicago Hoped to Generate Millions with Expensive City Sticker Tickets. It Didn't Work." WBEZ Interactive. Accessed February 28, 2022

Unfortunately, a more detailed analysis of unit practices based on specific enforcer strategies and individual results was outside the scope of this study due to privacy concerns, but this type of analysis remains a rich avenue for future exploration by policymakers with access to confidential data.

Looking back on how the 2012 City Sticker price hike was administered by different units reveals how the presence of third-party enforcers can benefit citizens by mitigating increases in transportation inequity when public officials have multi-faceted incentives for enforcement. The results of the study suggest policymakers should look to more creative avenues of increasing operating revenue, which may include cutting costs by entering highly accountable public-private partnerships, as potentially more equitable solutions than debates about price level paired with increased enforcement.

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Community Data Snapshots

<u>7. Appendix 1: Additional Tables and Figures</u>

1. Introduction

Figure 1.2: Chicago Ethnic Distribution

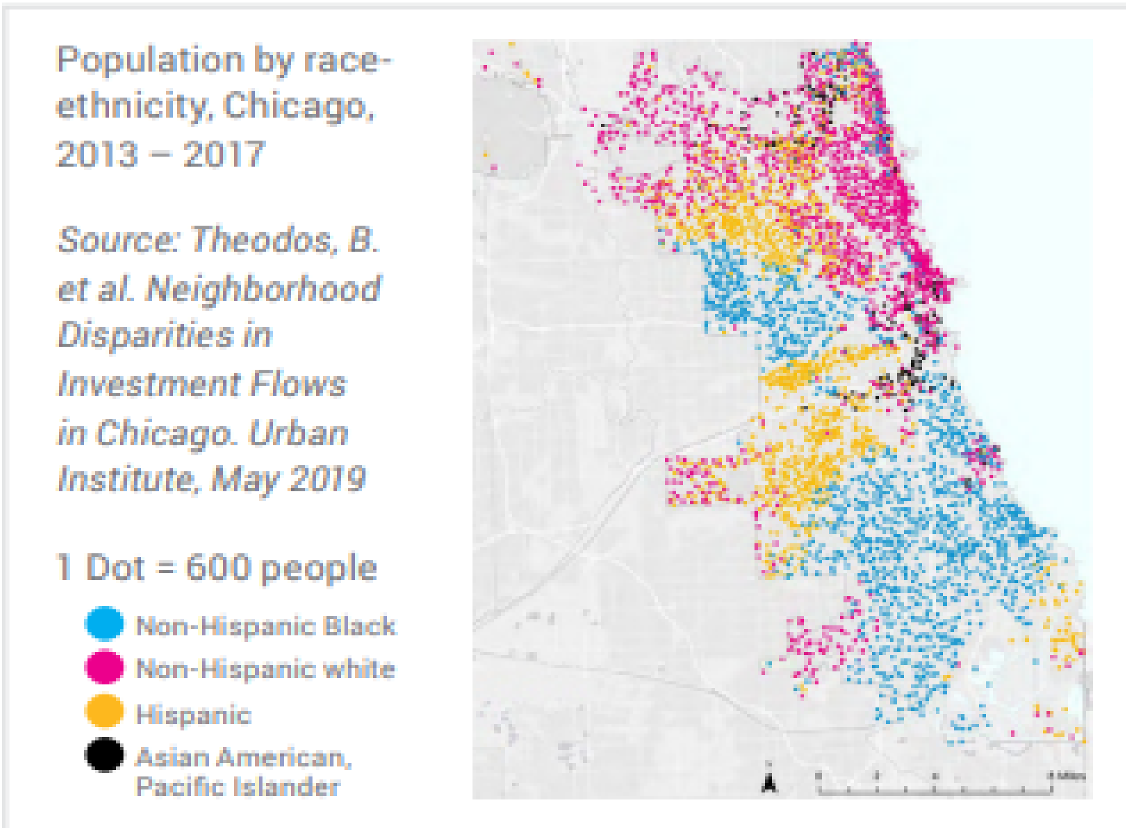


Figure 1.3: Chicago Transportation Cost

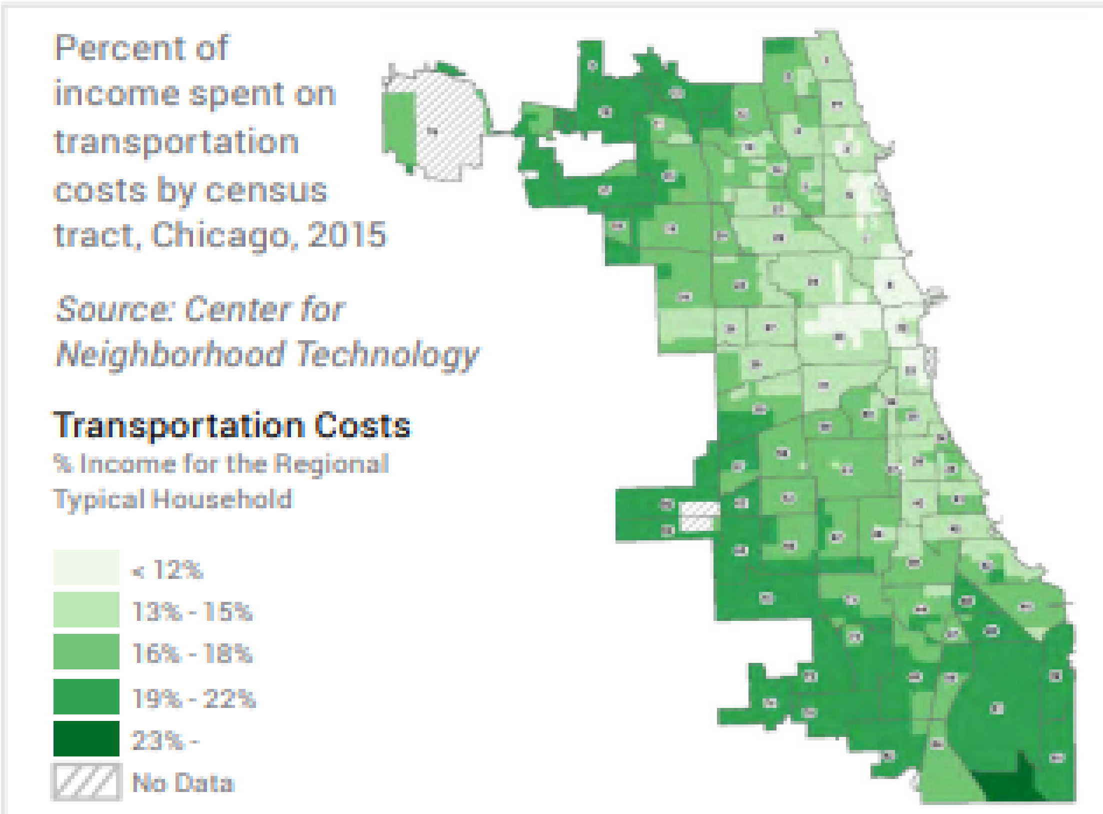
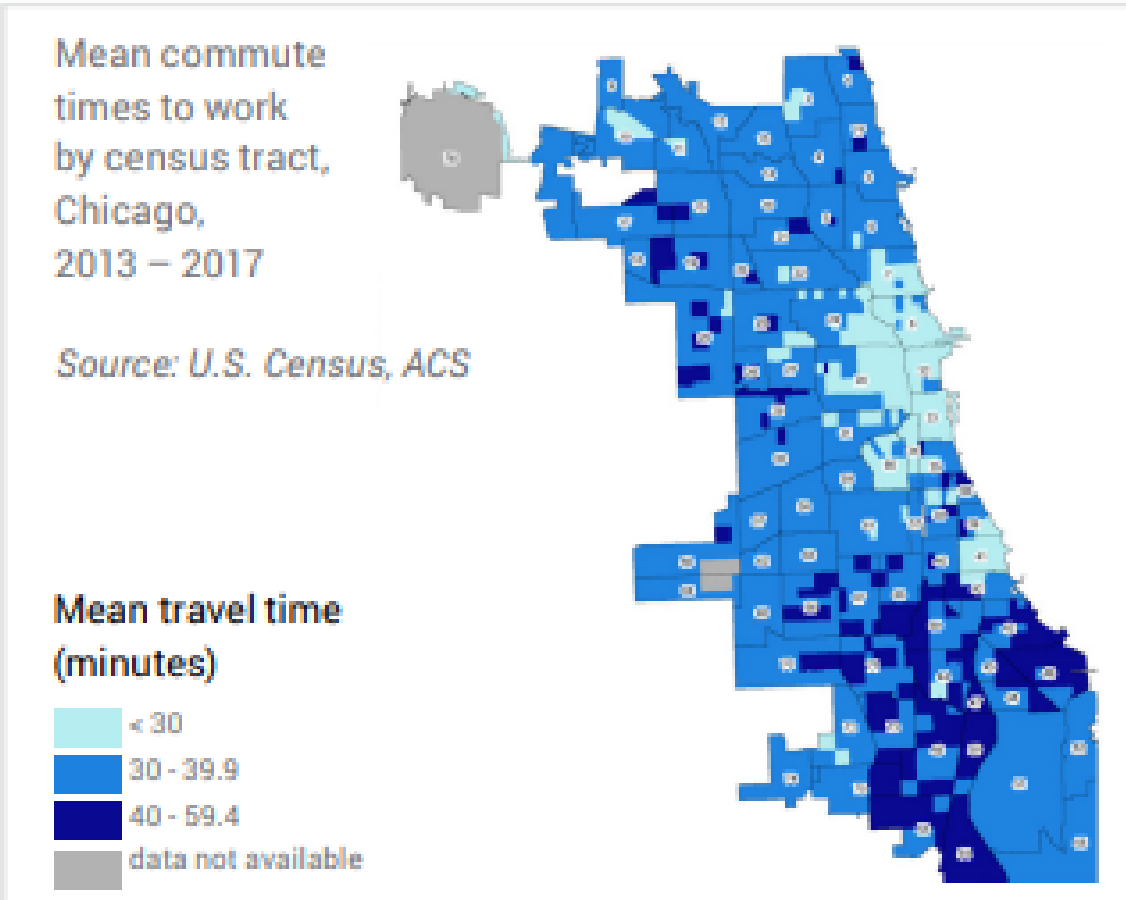


Figure 1.5: Chicago Commute Times



3. Methods

Figure 3.3.1 Unit Patterns With DOF

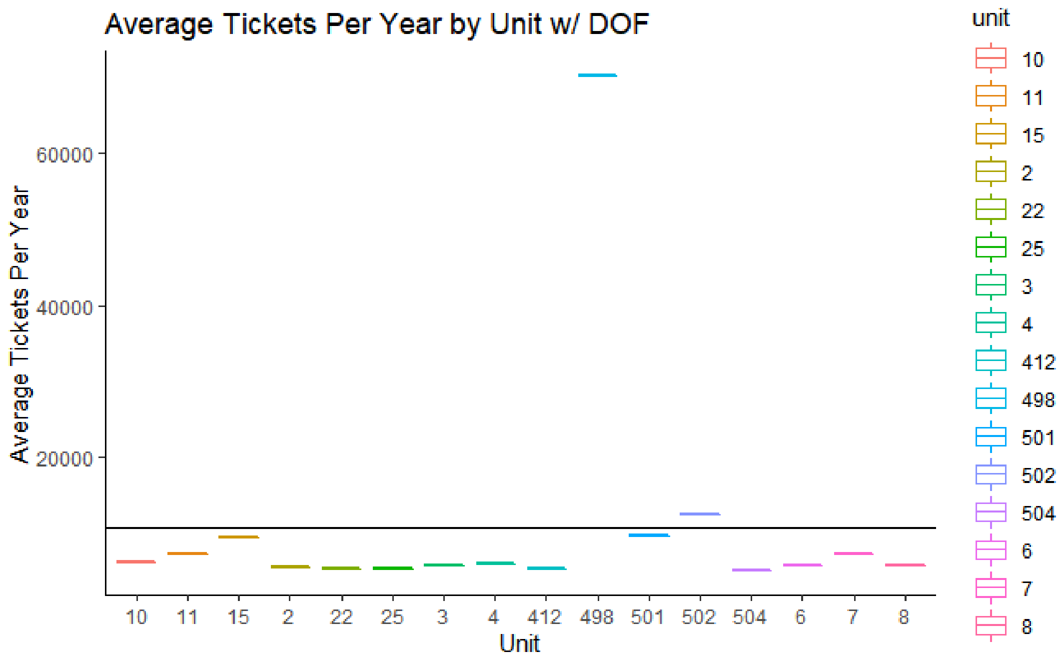


Figure 3.3.2 Unit Patterns Without DOF

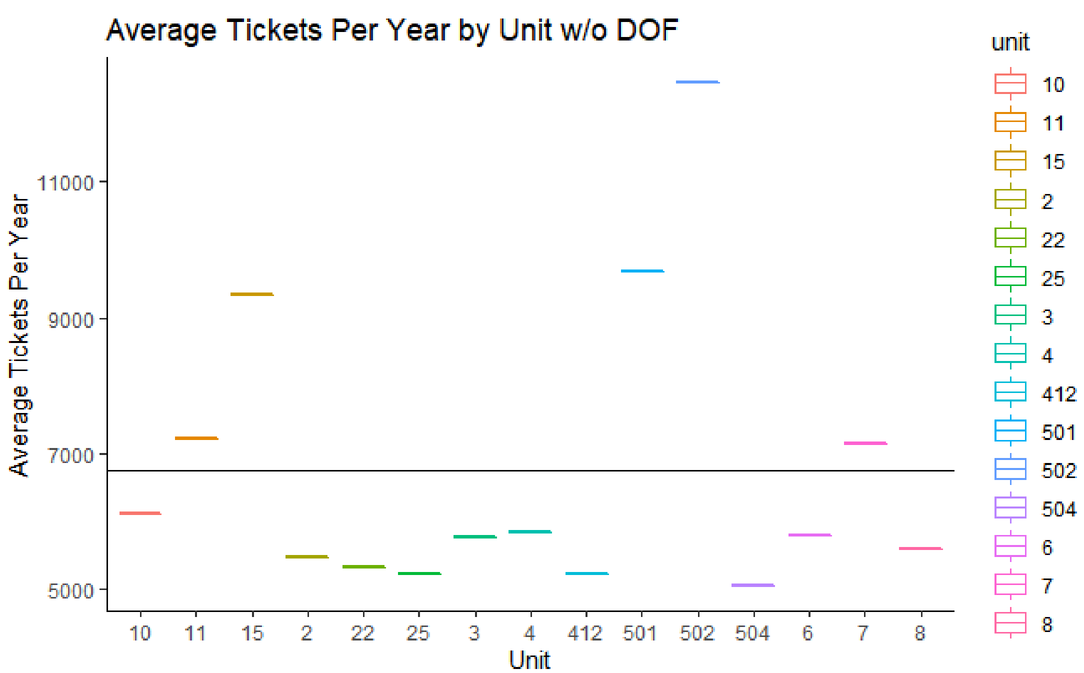


Figure 3.5: Average Tickets Per Year By Community Area

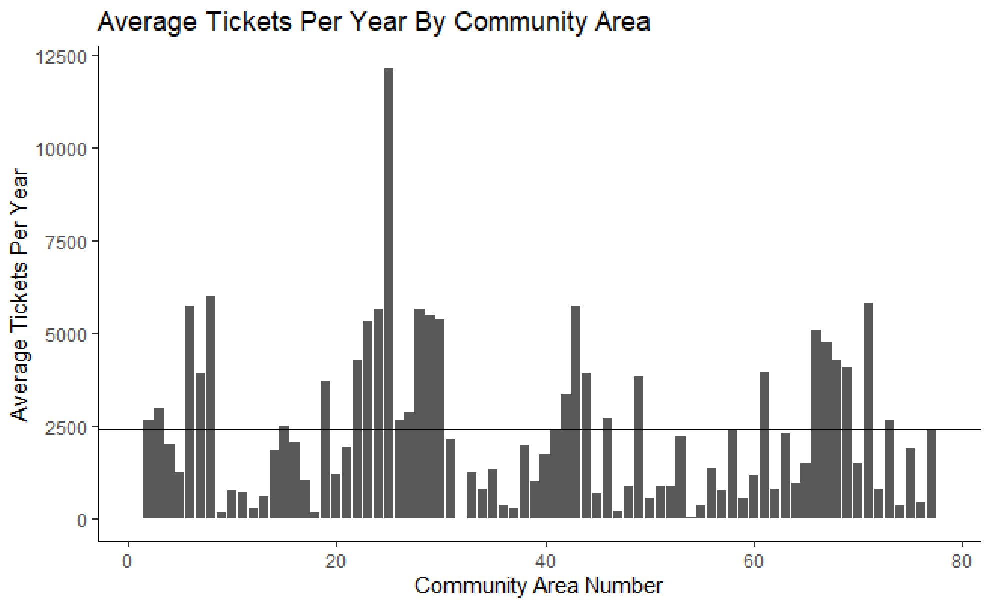


Figure 3.6 Average Tickets per Year by Community Area - Minimum 2500 Tickets

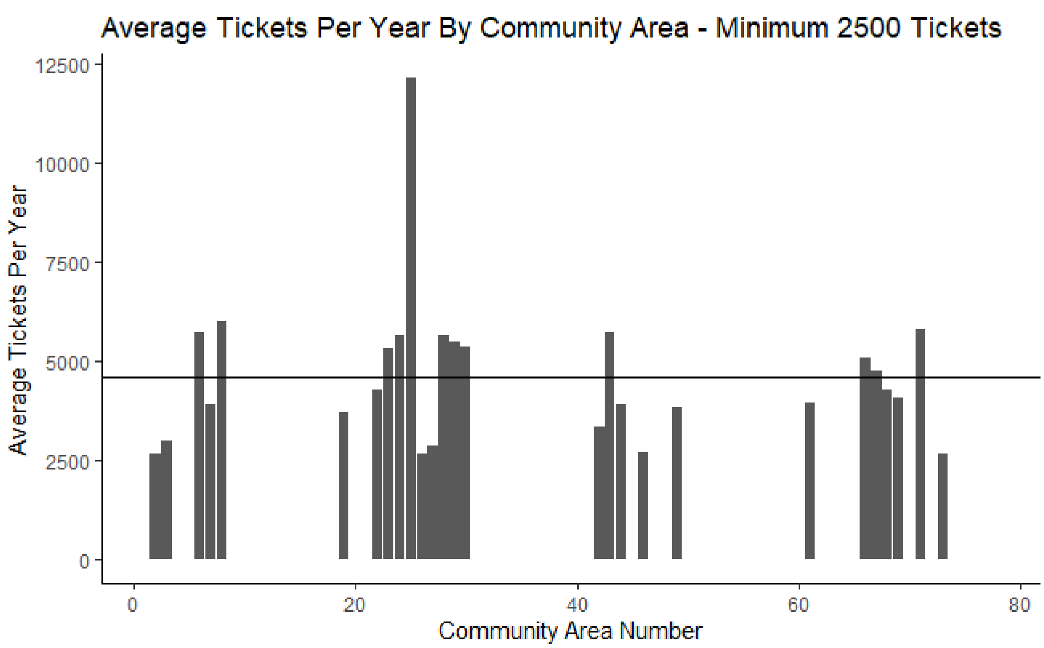
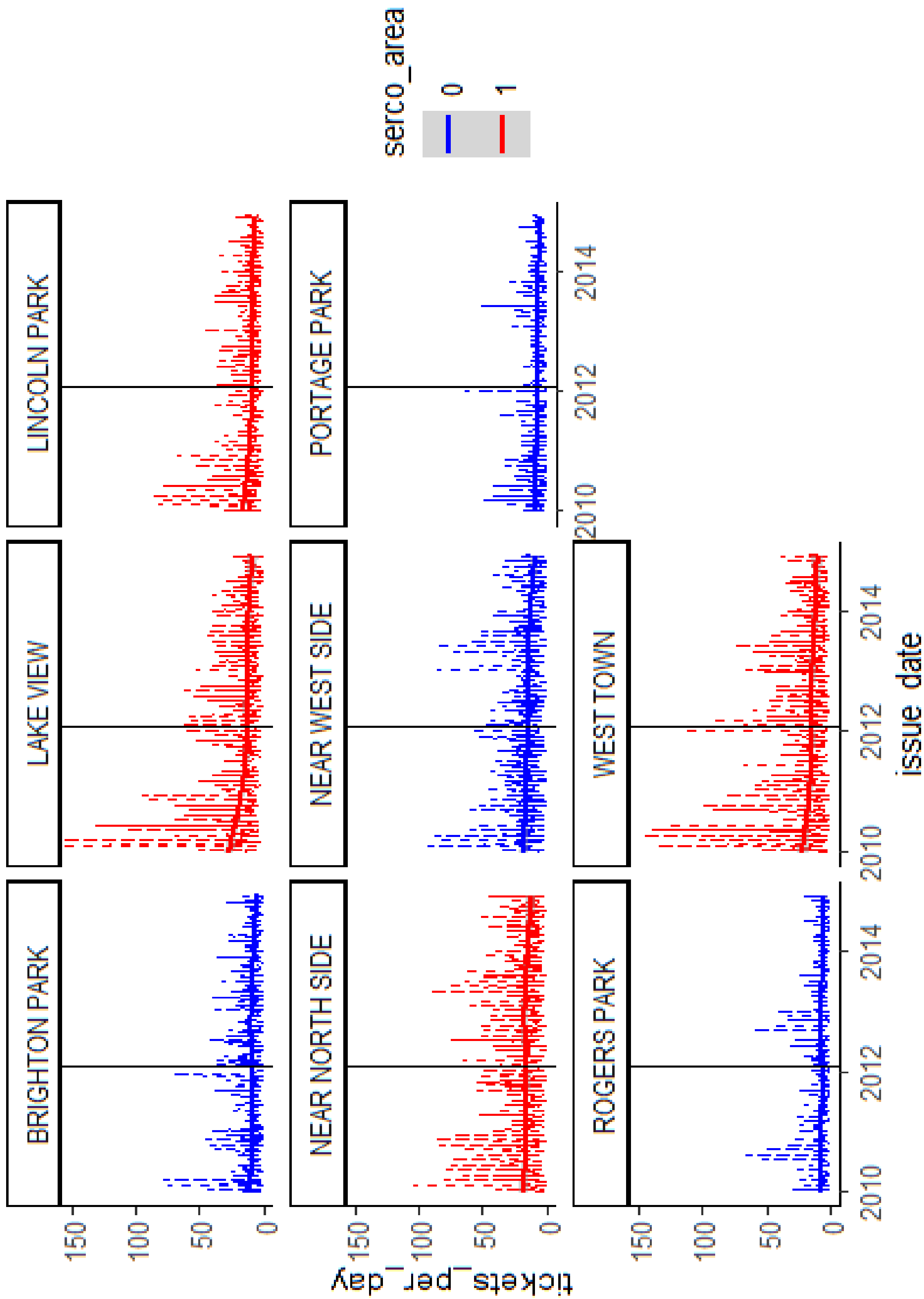


Figure 3.7 Parallel Trends By Neighborhood



8. Appendix 2: Code to Reproduce the Study

Jasper Snowden

1/31/2022

Downloading and Cleaning the Data

```
## Loading the Required Libraries
#  Core Packages
library(tidyverse)
library(readr)
library(here)

# Dating Manipulation
library(lubridate)

# Data Visualization
library(kableExtra)
library(ggforce)

# Data Analysis
library(did)
```

```
## Command to Render the Data Tidying R Script
## This combines the community profile data with the city sticker data
## Run this command(without the quotations) to combine the data sets: "rmarkdown::render("data_tidying.R")"
```

Loading in the Chicago City Sticker Ticket Data from the Folder

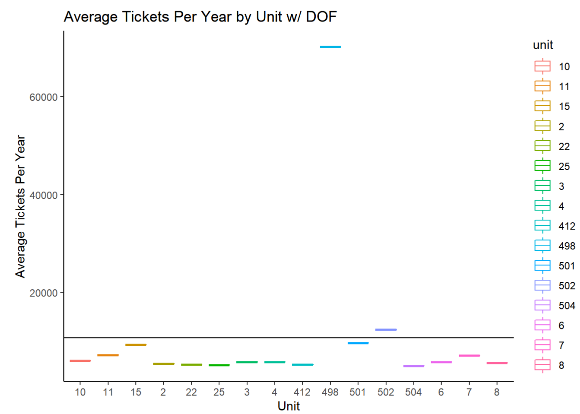
```
## Using the Readr package to load the chi_tickets df
#  Explcitly defining the column types to help prep the data for the model
chi_tickets <- read_csv("tidy_data/chi_tickets.csv",
    col_types = cols(after_holiday = col_logical(),
        annual_vehicle_miles = col_number(),
        asian = col_number(),
        before_holiday = col_logical(),
        black = col_number(),
        blockgroup_geoid = col_character(),
        carpool = col_number(),
        comm_other = col_number(),
        current_amount_due = col_number(),
        day = col_double(),
        drove_alone = col_number(),
        fine_level1_amount = col_number(),
        fine_level2_amount = col_number(),
        geocoded_lat = col_number(),
        geocoded_lng = col_number(),
        hisp = col_number(),
        holiday = col_logical(),
        hour = col_double(),
        license_plate_number = col_character(),
        license_plate_type = col_character(),
        med_inc = col_number(),
        month = col_double(),
        notice_level = col_character(),
        notice_number = col_character(),
        officer = col_character(),
        other = col_number(),
        park_access = col_number(),
        ticket_number = col_character(),
        ticket_queue = col_character(),
        ticket_queue_date = col_character(),
        ticket_revenue = col_number(),
        total_commuters = col_number(),
        total_payments = col_number(),
        total_penalties = col_number(),
        tract_id = col_character(),
        transit = col_number(),
        two_days_after_holiday = col_logical(),
        unit = col_character(),
        unit_description = col_character(),
        vehicle_make = col_character(),
        violation_code = col_character(),
        violation_description = col_character(),
        walk_bike = col_number(),
        ward = col_character(),
        white = col_number(),
        work_at_home = col_number(),
        year = col_double(),
        zipcode = col_character()))%>%
   filter(year %in% (2010:2014))
```

Filtering the Data to Years, Areas, and Units Most Relevant to the 2012 Policy Change

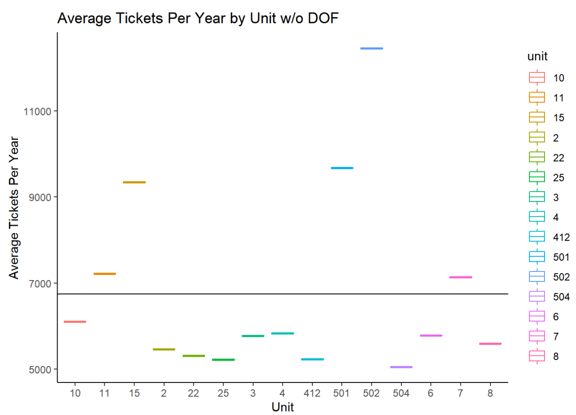
```
## Filtering the data to Unit Tickets by year to explore the relationship between unit and total tickets
# Dropping units that issue less than 4500 tickets in a year (This leaves me with the top 15 units)
unit_tickets_per_year <- chi_tickets %>%
  group_by(unit, year)%>%
  count()%>%
  rename(total_tickets = "n") %>%
  filter(total_tickets > 4500)%>%
  group_by(unit)%>%
  summarise(mean(total_tickets))%>%
  rename(total_tickets = 'mean(total_tickets)')%>%
  arrange(desc(total_tickets))%>%
  slice(1:25)


unit_tickets_per_year_table <- unit_tickets_per_year %>%
  kbl()%>%
  kable_styling()

unit_tickets_per_year_table
```

unit	total_tickets
498	70206.400
502	12461.400
501	9676.250
15	9345.000
11	7221.000
7	7138.750
10	6105.000
4	5828.000
6	5780.333
3	5774.500
8	5589.000
2	5464.000
22	5312.000
412	5234.000
25	5217.000
504	5054.000

```
remove(unit_tickets_per_year_table)


## The Top Units only produce a fraction of what the DOF does is tickets per year. I will try to keep these proport
ions in mind when deciding on control and experiment groups
## DOF = 40%
## Serco = 10%
## CPD (Total) = 38%
## CPD (Mean) = 4%

unit_tickets_boxplot <- unit_tickets_per_year%>%
  ggplot(mapping = aes(x = unit,
                       y = total_tickets,
                       color = unit))+
  geom_boxplot(outlier.color = "red")+
  geom_hline(aes(yintercept= mean(total_tickets)))+
  xlab("Unit")+
  ylab("Average Tickets Per Year")+
  ggtitle("Average Tickets Per Year by Unit w/ DOF")+
  theme_classic()

plot(unit_tickets_boxplot)
```




```
## The DOF is by and large the greatest single unit originator of tickets

## Recreating the boxplot without the DOF to clarify the results
unit_tickets_boxplot_no_dof <- unit_tickets_per_year%>%
  filter(unit != "498")%>%
  ggplot(mapping = aes(x = unit,
                       y = total_tickets,
                       color = unit))+
  geom_boxplot(outlier.color = "red")+
  geom_hline(aes(yintercept= mean(total_tickets)))+
  xlab("Unit")+
  ylab("Average Tickets Per Year")+
  ggtitle("Average Tickets Per Year by Unit w/o DOF")+
  theme_classic()

plot(unit_tickets_boxplot_no_dof)
```




```
remove(unit_tickets_boxplot, unit_tickets_boxplot_no_dof)
remove(unit_tickets_per_year)
## As can be seen from the first boxplot unit 498 (Chicago DOF) consitently issues the most tickets per unit over t
he time period
## When viewed without the department of finance the average of the dataset is about 6000 tickets per unit


# The DOF (498) City Clerk Office (501) and Serco - Private Contractor (502) are on average the greatest originator
s of city sticker tickets with some CPD units following like Austin and East Garfield Park.

# These CPD units are variable with different jurisdictions beyond one community area. I will not be analyzing CPD
 practices but this is an important fact to keep in mind when creating peer groups.
```

Creating the Control and Experiment Peer Groups

```
## Checking for community areas where serco was most active and least active
serco_tickets <- chi_tickets %>%
  filter(unit == "502" | unit == "504")%>%
  group_by(community_area_name, year)%>%
  count()%>%
  rename(total_tickets = "n")%>%
  group_by(community_area_name)%>%
  summarise(mean(total_tickets))%>%
  rename(mean_tickets ='mean(total_tickets)')%>%
  arrange(desc(mean_tickets))

serco_tickets_tbl <- serco_tickets %>%
  slice(1:25)%>%
  kbl()%>%
  kable_styling()
serco_tickets_tbl
```

community_area_name	mean_tickets
LAKE VIEW	2220.8
NEAR NORTH SIDE	1995.8
WEST TOWN	1574.2
LINCOLN PARK	1544.6
NEAR WEST SIDE	820.0
LOGAN SQUARE	706.8
EDGEWATER	438.4
SOUTH LAWNDALE	423.0
UPTOWN	398.4
LINCOLN SQUARE	327.8
NEAR SOUTH SIDE	326.4
AUSTIN	324.8
WEST RIDGE	323.2
ALBANY PARK	315.8
BELMONT CRAGIN	301.2
LOWER WEST SIDE	257.2
NORTH CENTER	239.8
AVONDALE	215.4
HYDE PARK	214.2
BRIDGEPORT	203.8
AUBURN GRESHAM	199.2
PORTAGE PARK	188.6
IRVING PARK	181.8
HUMBOLDT PARK	181.0
ARMOUR SQUARE	178.2

```
remove(serco_tickets_tbl)

## Repeating the above excercise for the CPD units
cpd_tickets <- chi_tickets %>%
  filter(unit == "15" | unit == "11" |
         unit == "10" | unit == "4" |
         unit == "6" | unit == "3" |
         unit == "8" | unit == "2" |
         unit == "22" | unit == "412" |
          unit == "25")%>%
  group_by(community_area_name, year)%>%
  count()%>%
  rename(total_tickets = "n")%>%
  group_by(community_area_name)%>%
  summarise(mean(total_tickets))%>%
  rename(mean_tickets ='mean(total_tickets)')%>%
  arrange(desc(mean_tickets))

cpd_tickets_tbl <-cpd_tickets %>%
  slice(1:25)%>%
  kbl()%>%
  kable_styling()
cpd_tickets_tbl
```

community_area_name	mean_tickets
AUSTIN	7921.4
NORTH LAWNDALE	3857.8
AUBURN GRESHAM	2938.4
CHICAGO LAWN	2168.8

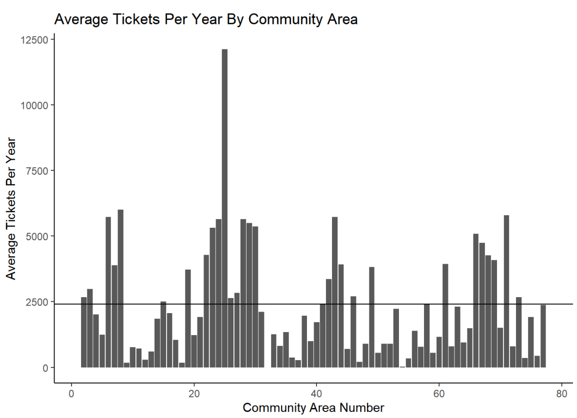
community_area_name	mean_tickets
HUMBOLDT PARK	1930.2
SOUTH SHORE	1916.2
WOODLAWN	1799.2
WASHINGTON HEIGHTS	1736.8
GREATER GRAND CROSSING	1735.8
WEST GARFIELD PARK	1654.6
CHATHAM	1624.4
EAST GARFIELD PARK	1547.4
MORGAN PARK	1459.8
GRAND BOULEVARD	1270.0
SOUTH CHICAGO	1238.4
WASHINGTON PARK	1189.4
BELMONT CRAGIN	1123.2
SOUTH LAWNDALE	1111.4
ROSELAND	838.0
SOUTH DEERING	582.4
ASHBURN	511.4
ENGLEWOOD	504.2
BEVERLY	485.6
GARFIELD RIDGE	482.0
GAGE PARK	427.2

```
remove(cpd_tickets_tbl)

## Repeating the above excercise for the City Units
city_tickets <- chi_tickets %>%
  filter(unit == "498" | unit == "501")%>%
  group_by(community_area_name, year)%>%
  count()%>%
  rename(total_tickets = "n")%>%
  group_by(community_area_name)%>%
  summarise(mean(total_tickets))%>%
  rename(mean_tickets ='mean(total_tickets)')%>%
  arrange(desc(mean_tickets))

city_tickets_tbl <- city_tickets %>%
  slice(1:25)%>%
  kbl()%>%
  kable_styling()
city_tickets_tbl
```

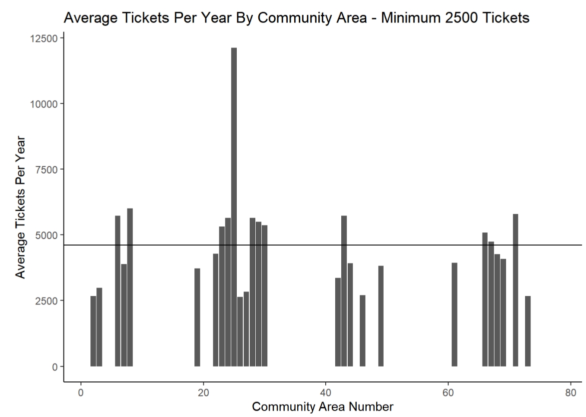
community_area_name	mean_tickets
SOUTH LAWNDALE	3773.2
AUSTIN	3472.4
SOUTH SHORE	3360.8
WEST TOWN	2986.0

community_area_name	mean_tickets
NEAR WEST SIDE	2916.0
NEAR NORTH SIDE	2762.6
CHICAGO LAWN	2496.6
LOGAN SQUARE	2431.4
AUBURN GRESHAM	2280.6
HUMBOLDT PARK	2235.6
BELMONT CRAGIN	2218.6
LAKE VIEW	2144.8
CHATHAM	1917.4
BRIGHTON PARK	1783.0
LINCOLN PARK	1662.4
GAGE PARK	1596.8
HYDE PARK	1552.8
GREATER GRAND CROSSING	1467.2
NEW CITY	1437.6
PORTAGE PARK	1434.2
LOWER WEST SIDE	1406.2
ROSELAND	1325.0
IRVING PARK	1239.6
SOUTH CHICAGO	1174.4
NORTH LAWNDALE	1168.0

```
remove(city_tickets_tbl)
## Serco is most active in Lakeview, Near North Side, West Town, Lincoln Park, Near West Side, and Logan Square

## City Units are most active in South Lawndale, Austin, South Shore, West Town, Near West Side, and Near North Sid
e

## CPD is most active in Austin, North Lawndale, Auburn Gresham, Chicao Lawn, Humboldt Park, and South Shore



#### Confirming Serco is the primary ticketer in the Experiment Group and that DOF is the primary ticketer in the c
ontrol ############################################

## Finding the average tickets issued by community area to create a minimum level of tickets for the community area
s in the study
cca_avgs <- chi_tickets %>%
  group_by(community_area_number, year)%>%
  count()%>%
  rename(tickets_per_cca = 'n')%>%
  mutate(tickets_per_cca = as.numeric(tickets_per_cca), .keep = "unused")%>%
  group_by(community_area_number)%>%
  summarise(mean(tickets_per_cca))%>%
  rename(avg_tickets_per_cca = 'mean(tickets_per_cca)')%>%
  ggplot(mapping = aes(x = community_area_number,
                   y = avg_tickets_per_cca))+
  geom_col()+
  geom_hline(aes(yintercept= mean(avg_tickets_per_cca)))+
 xlab("Community Area Number")+
 ylab("Average Tickets Per Year")+
 ggtitle("Average Tickets Per Year By Community Area")+
  xlim(1,78)+
  theme_classic()

plot(cca_avgs)
```




```
remove(cca_avgs)

## The Average total tickets are around 2500 oer community area. Running the above analysis with only community are
as issuing atleast the avg number of tickets
cca_avgs_top_cca <- chi_tickets %>%
  group_by(community_area_number, year)%>%
  count()%>%
  rename(tickets_per_cca = 'n')%>%
  mutate(tickets_per_cca = as.numeric(tickets_per_cca), .keep = "unused")%>%
  group_by(community_area_number)%>%
  summarise(mean(tickets_per_cca))%>%
  rename(avg_tickets_per_cca = 'mean(tickets_per_cca)')%>%
  filter(avg_tickets_per_cca >= 2500)%>%
  ggplot(mapping = aes(x = community_area_number,
                   y = avg_tickets_per_cca))+
  geom_col()+
  geom_hline(aes(yintercept= mean(avg_tickets_per_cca)))+
 xlab("Community Area Number")+
 ylab("Average Tickets Per Year")+
 ggtitle("Average Tickets Per Year By Community Area - Minimum 2500 Tickets")+
  xlim(1,78)+
  theme_classic()


plot(cca_avgs_top_cca)
```




```
remove(cca_avgs_top_cca)

## Viewing the plot as a table
cca_avgs_top_cca_table <- chi_tickets %>%
  group_by(community_area_name, community_area_number, year)%>%
  count()%>%
  rename(tickets_per_cca = 'n')%>%
  mutate(tickets_per_cca = as.numeric(tickets_per_cca), .keep = "unused")%>%
  group_by(community_area_name, community_area_number)%>%
  summarise(mean(tickets_per_cca))%>%
  rename(avg_tickets_per_cca = 'mean(tickets_per_cca)')%>%
  filter(avg_tickets_per_cca >= 2000)%>%
  arrange(desc(avg_tickets_per_cca))%>%
  slice(1:25)

cca_avgs_top_cca_table
```

```
## # A tibble: 37 x 3
## # Groups:   community_area_name [37]
##    community_area_name community_area_number avg_tickets_per_cca
##    <chr>                               <dbl>               <dbl>
##  1 AUBURN GRESHAM                         71               5796.
##  2 AUSTIN                                 25              12121
##  3 BELMONT CRAGIN                         19               3719.
##  4 BRIGHTON PARK                          58               2407.
##  5 CHATHAM                                44               3926.
##  6 CHICAGO LAWN                           66               5089.
##  7 EAST GARFIELD PARK                     27               2839.
##  8 EDGEWATER                              77               2376
##  9 ENGLEWOOD                              68               4258.
## 10 GAGE PARK                              63               2307.
## # ... with 27 more rows
```

```
## The Averages of these community areas is much closer to 4000.
## Finding what percentage of tickets are initiated by each unit in each community area for the benchmark compariso
n

serco_cca_select <- chi_tickets %>%
  group_by(community_area_name, unit, year)%>%
  count()%>%
  rename(tickets = 'n')%>%
  mutate(tickets = as.numeric(tickets),
         .keep = "unused")%>%
  mutate(serco_tickets = if_else(unit == "502" |unit == "504",
                                 tickets, 0))%>%
  group_by(community_area_name, year)%>%
  mutate(pct_serco = 1000 *(serco_tickets/ sum(tickets)))%>%
  group_by(community_area_name)%>%
  filter(sum(tickets) > 2000)%>%
  summarise(mean(pct_serco))%>%
  rename(percent_serco_enforced = 'mean(pct_serco)')%>%
  arrange(desc(percent_serco_enforced))%>%
  slice(1:25)

serco_cca_select
```

```
## # A tibble: 25 x 2
##    community_area_name percent_serco_enforced
##    <chr>                                <dbl>
##  1 LINCOLN PARK                         22.2
##  2 LAKE VIEW                            20.2
##  3 EDGEWATER                            18.0
##  4 ARMOUR SQUARE                        14.9
##  5 NEAR SOUTH SIDE                      14.0
##  6 NORTH CENTER                         13.9
##  7 ALBANY PARK                          12.5
##  8 LINCOLN SQUARE                       10.7
##  9 UPTOWN                               10.3
## 10 NEAR NORTH SIDE                       9.97
## # ... with 15 more rows
```

```
## city Activity
city_cca_select <- chi_tickets %>%
  group_by(community_area_name, unit, year)%>%
  count()%>%
  rename(tickets = 'n')%>%
  mutate(tickets = as.numeric(tickets),
         .keep = "unused")%>%
  mutate(dof_tickets = if_else(unit == "501" | unit == "498",
                               tickets,  0 ))%>%
  group_by(community_area_name, year)%>%
  mutate(pct_dof = 1000* (dof_tickets/ sum(tickets)))%>%
  group_by(community_area_name)%>%
  filter(sum(tickets) > 2000)%>%
  filter(sum(dof_tickets) > 800)%>%
  summarise(mean(pct_dof))%>%
  rename(percent_dof_enforced = 'mean(pct_dof)')%>%
  arrange(desc(percent_dof_enforced))%>%
  slice(1:25)

# CPD Activity
cpd_cca_select <- chi_tickets %>%
  group_by(community_area_name, unit, year)%>%
  count()%>%
  rename(tickets = 'n')%>%
  mutate(tickets = as.numeric(tickets),
         .keep = "unused")%>%
  mutate(cpd_tickets = if_else(unit == "15" |
                               unit == "11" |
                               unit == "10" |
                               unit == "4" |
                               unit == "6" |
                               unit == "3" |
                               unit == "8" |
                               unit == "2" |
                               unit == "22" |
                               unit == "412" |
                               unit == "25",
                               tickets, 0))%>%
  group_by(community_area_name, year)%>%
  mutate(pct_cpd = 1000 *(cpd_tickets/ sum(tickets)))%>%
  group_by(community_area_name)%>%
  filter(sum(tickets) > 2500)%>%
  summarise(mean(pct_cpd))%>%
  rename(percent_cpd_enforced = 'mean(pct_cpd)')%>%
  arrange(desc(percent_cpd_enforced))%>%
  slice(1:25)

cpd_cca_select
```

```
## # A tibble: 25 x 2
##    community_area_name percent_cpd_enforced
##    <chr>                              <dbl>
##  1 BEVERLY                             55.8
##  2 MORGAN PARK                         53.6
##  3 EAST SIDE                           46.2
##  4 SOUTH DEERING                       36.2
##  5 WASHINGTON HEIGHTS                  31.4
##  6 AVALON PARK                         26.5
##  7 CLEARING                            24.9
##  8 WEST ELSDON                         24.1
##  9 HERMOSA                             23.8
## 10 GRAND BOULEVARD                     22.7
## # ... with 15 more rows
```

```
## Combining the observations into one table to decide on a peer group
## Criteria: Average or higher serco enforcement for Serco neighborhoods
## (i.e., 10% or more)
## Criteria: Less than 7% Serco enforced for City Neighborhoods +
## Less than 15% police enforced for City Neighborhoods

serco_cca_select_comparison <- cpd_cca_select%>%
  left_join(serco_cca_select , by = "community_area_name")%>%
  left_join(city_cca_select, by = "community_area_name")%>%
  left_join(cca_avgs_top_cca_table, by = "community_area_name")%>%
  slice(1:25)%>%
  kbl()%>%
  kable_styling()

city_cca_select
```

```
## # A tibble: 25 x 2
##    community_area_name percent_dof_enforced
##    <chr>                              <dbl>
##  1 WEST ELSDON                         68.9
##  2 EAST SIDE                           65.1
##  3 WEST LAWN                           57.1
##  4 ARCHER HEIGHTS                      56.7
##  5 MCKINLEY PARK                       53.5
##  6 HERMOSA                             51.2
##  7 NORTH PARK                          51.2
##  8 AVALON PARK                         49.4
##  9 CLEARING                            45.3
## 10 HYDE PARK                           45.3
## # ... with 15 more rows
```

```
serco_cca_select_comparison
```

community_area_name	percent_cpd_enforced	percent_serco_enforced	percent_dof_enforced	community_area_number
BEVERLY	55.81120	NA	31.95461	NA
MORGAN PARK	53.57203	NA	NA	NA
EAST SIDE	46.23403	7.029897	65.05998	NA
SOUTH DEERING	36.17305	NA	NA	NA
WASHINGTON HEIGHTS	31.39245	NA	NA	73
AVALON PARK	26.47246	NA	49.36141	NA
CLEARING	24.87912	NA	45.29758	NA
WEST ELSDON	24.10455	5.411620	68.90874	NA
HERMOSA	23.78610	9.261598	51.24652	NA
GRAND BOULEVARD	22.72895	NA	NA	NA
KENWOOD	22.05983	NA	NA	NA
ARCHER HEIGHTS	21.17672	4.539756	56.70331	NA
GARFIELD RIDGE	20.65676	NA	31.07424	NA
WEST LAWN	20.04802	NA	57.07698	NA
WEST GARFIELD PARK	19.91864	NA	NA	26
CALUMET HEIGHTS	19.57527	NA	42.20261	NA
NORTH LAWNDALE	19.55094	NA	NA	29
WASHINGTON PARK	19.50849	NA	NA	NA
ASHBURN	19.03123	NA	33.01770	NA
EAST GARFIELD PARK	15.86634	NA	NA	27
AUSTIN	14.78896	NA	NA	25
SOUTH CHICAGO	14.77846	NA	NA	46
AUBURN GRESHAM	14.75434	NA	NA	71
DOUGLAS	14.32000	NA	NA	NA
CHATHAM	12.92520	NA	NA	44

```
## The Serco neighborhoods will be LAKE VIEW, NEAR NORTH SIDE", "WEST TOWN", & "LINCOLN PARK"

## The City neighborhoods will be BRIGHTON PARK, NEAR WEST SIDE, ROGERS PARK, & PORTAGE PARK



remove(city_cca_select)
remove(serco_cca_select)
remove(cpd_cca_select)
remove(serco_cca_select_comparison)
remove(cca_avgs_top_cca_table)
```

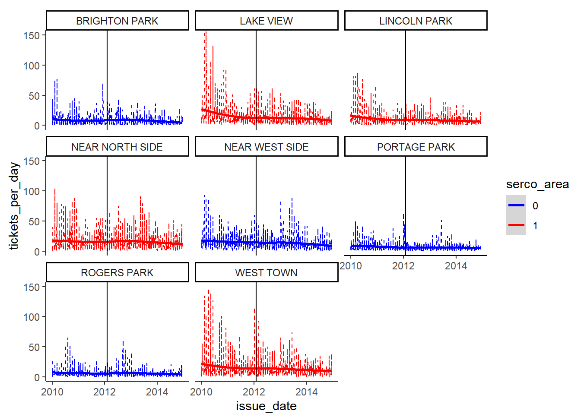
Confirming The Parallel Trends Assumption

```
## Confirming the Parellel Trends Assumption for these neighborhoods
## Creating a data frame with and indicator for control vs experiment group
serco_trends <- chi_tickets %>%
  filter(community_area_name == "LAKE VIEW"|
         community_area_name == "NEAR NORTH SIDE"|
         community_area_name == "WEST TOWN"|
         community_area_name == "LINCOLN PARK"|
         community_area_name == "BRIGHTON PARK"|
         community_area_name == "NEAR WEST SIDE"|
         community_area_name == "ROGERS PARK"|
         community_area_name == "PORTAGE PARK")%>%
  mutate(serco_area = if_else(
    community_area_number %in% c("6", "7", "8", "24"), 1, 0))


## Average Tickets over the time period
serco_trends_mean_tickets <- serco_trends %>%
  group_by(community_area_name, year)%>%
  count()%>%
  rename(total_tickets = "n")%>%
  group_by(community_area_name)%>%
  summarise(mean(total_tickets))%>%
  rename(mean_tickets ='mean(total_tickets)')%>%
  arrange(desc(mean_tickets))

serco_trends_mean_tickets_tbl <- serco_trends_mean_tickets%>%
  kbl()%>%
  kable_styling()

serco_trends_mean_tickets_tbl
```

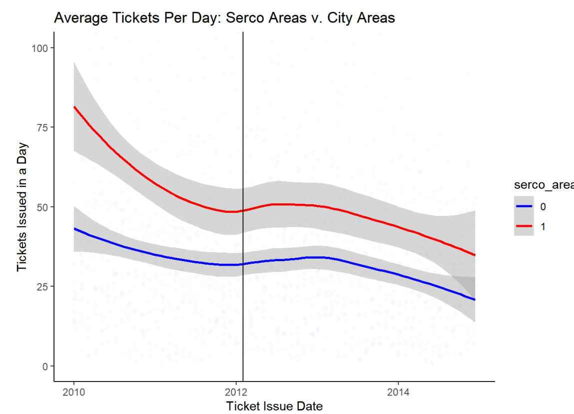
community_area_name	mean_tickets
NEAR NORTH SIDE	6004.2
LAKE VIEW	5717.0
WEST TOWN	5648.2
NEAR WEST SIDE	5639.4
LINCOLN PARK	3891.2

community_area_name	mean_tickets
PORTAGE PARK	2498.0
BRIGHTON PARK	2406.8
ROGERS PARK	2245.2

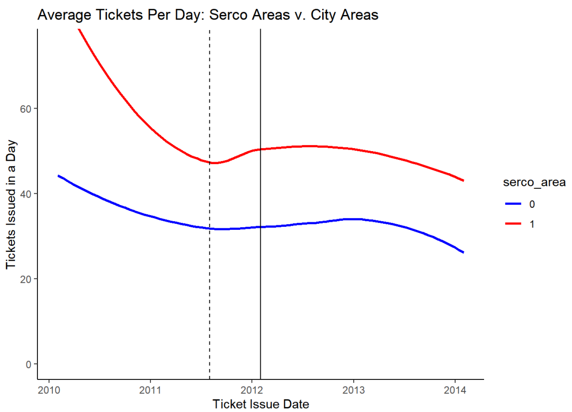
```
remove(serco_trends_mean_tickets, serco_trends_mean_tickets_tbl)

## Image of the parallel trends assumption test. As can be seen from the community area plots, trends are consisten
t between neighborhoods and different between control and experiment groups
serco_trends_linegraphs <- serco_trends %>%
   mutate(issue_date = as.Date(issue_date, "%d/%m/%Y"),.keep = "unused")%>%
  group_by(issue_date, community_area_name, serco_area)%>%
  count()%>%
  rename(tickets_per_day = "n")%>%
  mutate(serco_area = as.character(serco_area))%>%
  ggplot(mapping = aes(x = issue_date, y = tickets_per_day, color = serco_area))+
  scale_color_manual(values = c("blue", "red"))+
  geom_line(linetype = "dashed")+
  geom_smooth()+
  facet_wrap(~ community_area_name)+
  geom_vline(xintercept = as.Date("2012-02-01"))+
  coord_cartesian(ylim = c(0, 150))+
  theme_classic()

plot(serco_trends_linegraphs)
```



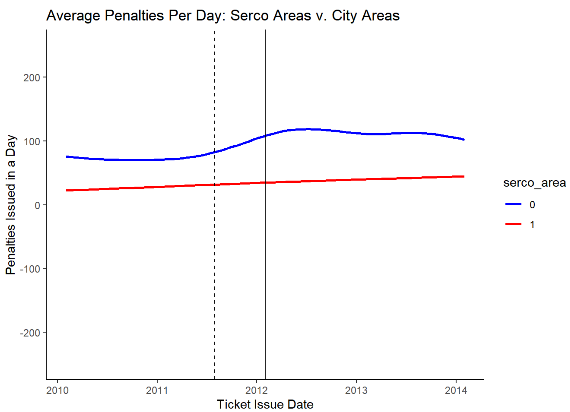

```
remove(serco_trends_linegraphs)


## Monthly Tickets over time
serco_trends_linegraph <- serco_trends %>%
   mutate(issue_date = as.Date(issue_date, "%d/%m/%Y"),.keep = "unused")%>%
  group_by(issue_date, serco_area)%>%
  count()%>%
  rename(tickets_per_day = "n")%>%
  mutate(serco_area = as.character(serco_area))%>%
  ggplot(mapping = aes(x = issue_date,
                      y = tickets_per_day,
                      color = serco_area),
         alpha = 0.01)+
  geom_point(linetype = "dashed", width = 0.1, alpha = 0.01)+
  scale_color_manual(values = c("blue", "red"))+
  geom_smooth()+
  geom_vline(xintercept = as.Date("2012-02-01"))+
  coord_cartesian(ylim = c(0, 100))+
  xlab("Ticket Issue Date")+
  ylab("Tickets Issued in a Day")+
  ggtitle("Average Tickets Per Day: Serco Areas v. City Areas")+
  theme_classic()

plot(serco_trends_linegraph)
```



```
remove(serco_trends_linegraph)

serco_trends_linegraph_point <- serco_trends %>%
   mutate(issue_date = as.Date(issue_date, "%d/%m/%Y"),.keep = "unused")%>%
  mutate(serco_area = as.character(serco_area))%>%
  group_by(issue_date, serco_area)%>%
  count()%>%
  rename(tickets_per_day = "n")%>%
  ggplot(mapping = aes(x = issue_date,
                       y = tickets_per_day,
                       color = serco_area))+
  scale_color_manual(values = c("blue", "red"))+
  geom_line(alpha = 0.001)+
  geom_smooth(se = F)+
  geom_vline(xintercept = as.Date("2012-02-01"))+
  geom_vline(xintercept = as.Date("2011-08-01"), linetype = "dashed")+
  coord_cartesian(ylim = c(0, 75))+
  scale_x_date(limits = as.Date(c("2010-02-01","2014-02-01")))+
  xlab("Ticket Issue Date")+
  ylab("Tickets Issued in a Day")+
  ggtitle("Average Tickets Per Day: Serco Areas v. City Areas")+
  theme_classic()

plot(serco_trends_linegraph_point)
```




```
remove(serco_trends_linegraph_point)

## Total Penalties
serco_rev_linegraph_point <- serco_trends %>%
   mutate(issue_date = as.Date(issue_date, "%d/%m/%Y"),.keep = "unused")%>%
  mutate(serco_area = as.character(serco_area))%>%
  group_by(issue_date, serco_area, community_area_name)%>%
  summarise(mean(total_penalties))%>%
  rename(penalties_per_day = 'mean(total_penalties)')%>%
  ggplot(mapping = aes(x = issue_date,
                       y = penalties_per_day,
                       color = serco_area))+
  scale_color_manual(values = c("blue", "red"))+
  geom_line(alpha = 0.001)+
  geom_smooth(se = F)+
  geom_vline(xintercept = as.Date("2012-02-01"))+
  geom_vline(xintercept = as.Date("2011-08-01"), linetype = "dashed")+
  scale_x_date(limits = as.Date(c("2010-02-01","2014-02-01")))+
  coord_cartesian(ylim = c(-250, 250))+
  xlab("Ticket Issue Date")+
  ylab("Penalties Issued in a Day")+
  ggtitle("Average Penalties Per Day: Serco Areas v. City Areas")+
  theme_classic()


plot(serco_rev_linegraph_point)
```




```
remove(serco_rev_linegraph_point)


## The Parellel Trends assumption appears to hold Neither group crosses over in terms of total tickets during the t
ime period though serco areas are clearly targeted for more penalties on average. As the community profile data is
 all stationary, it basically serves as an indicator variable in the study. It does not change over time and, thus,
no test of the parellel trends assumption is required for those variables



remove(serco_trends)
##  Now I am ready to run the first attempt at the difference and differences with the Lakeview, Near North Side, W
est Town, Lincoln Park, Near West Side and Near South Side as the testing group and Austin, Belmont Crighton, Humbo
ldt Park, Portagage Park and South Shore as the control group.
```

DID of Relationship Between SERCO and City Ticketing w/ Stated Policy Change Date

```r
## DID units and Neighborhoods
## Creating the Serco Data Frame with the selected experiment and control groups
# First to select the relevant variables to make the data set more tidy
# Outcome Variables: total_payments

serco_tidy_df <- chi_tickets %>%
    filter(community_area_name == "LAKE VIEW"|
         community_area_name == "NEAR NORTH SIDE"|
         community_area_name == "WEST TOWN"|
         community_area_name == "LINCOLN PARK"|
         community_area_name == "BRIGHTON PARK"|
         community_area_name == "NEAR WEST SIDE"|
         community_area_name == "ROGERS PARK"|
         community_area_name == "PORTAGE PARK")%>%
    filter(year %in% (2010:2014))%>%
  filter(total_payments >= 0)%>%
  mutate(total_penalties = if_else(current_amount_due >= 0,
           total_payments + current_amount_due - fine_level1_amount,
           total_payments - fine_level1_amount))%>%
  filter(total_penalties >= 0)%>%
  mutate(prct_penalty = total_penalties/fine_level1_amount)%>%
  select(-current_amount_due,
         -issue_date,
         -total_payments,
         -ticket_number,
         -fine_level1_amount,
         -fine_level2_amount)%>%
  mutate(community_area_number = as.character(community_area_number))%>%
  mutate(month_n = case_when(month == 2 & year == 2010 ~ "-24",
                             month == 3 & year == 2010 ~ "-23",
                             month == 4 & year == 2010 ~ "-22",
                             month == 5 & year == 2010 ~ "-21",
                             month == 6 & year == 2010 ~ "-20",
                             month == 7 & year == 2010 ~ "-19",
                             month == 8 & year == 2010 ~ "-18",
                             month == 9 & year == 2010 ~ "-17",
                             month == 10 & year == 2010 ~ "-16",
                             month == 11 & year == 2010 ~ "-15",
                             month == 12 & year == 2010 ~ "-14",
                             month == 1 & year == 2011 ~ "-13",
                             month == 2 & year == 2011 ~ "-12",
                             month == 3 & year == 2011 ~ "-11",
                             month == 4 & year == 2011 ~ "-10",
                             month == 5 & year == 2011 ~ "-9",
                             month == 6 & year == 2011 ~ "-8",
                             month == 7 & year == 2011 ~ "-7",
                             month == 8 & year == 2011 ~ "-6",
                             month == 9 & year == 2011 ~ "-5",
                             month == 10 & year == 2011 ~ "-4",
                             month == 11 & year == 2011 ~ "-3",
                             month == 12 & year == 2011 ~ "-2",
                             month == 1 & year == 2012 ~ "-1",
                             month == 2 & year == 2012 ~ "0",
                             month == 3 & year == 2012 ~ "1",
                             month == 4 & year == 2012 ~ "2",
                             month == 5 & year == 2012 ~ "3",
                             month == 6 & year == 2012 ~ "4",
                             month == 7 & year == 2012 ~ "5",
                             month == 8 & year == 2012 ~ "6",
                             month == 9 & year == 2012 ~ "7",
                             month == 10 & year == 2012 ~ "8",
                             month == 11 & year == 2012 ~ "9",
                             month == 12 & year == 2012 ~ "10",
                             month == 1 & year == 2013 ~ "11",
                             month == 2 & year == 2013 ~ "12",
                             month == 3 & year == 2013 ~ "13",
                             month == 4 & year == 2013 ~ "14",
                             month == 5 & year == 2013 ~ "15",
                             month == 6 & year == 2013 ~ "16",
                             month == 7 & year == 2013 ~ "17",
                             month == 8 & year == 2013 ~ "18",
                             month == 9 & year == 2013 ~ "19",
```

```r
                             month == 10 & year == 2013 ~ "20",
                             month == 11 & year == 2013 ~ "21",
                             month == 12 & year == 2013 ~ "22",
                             month == 1 & year == 2014 ~ "23",
                             month == 2 & year == 2014 ~ "24"))%>%
  filter(month_n != "NA")

serco_did <- serco_tidy_df %>%
  group_by(month_n)%>%
  mutate_at(c('prct_penalty'), ~(scale(.) %>% as.vector))%>%
  rename(prct_abv_mean_penalty = "prct_penalty")%>%
  mutate(prct_abv_mean_penalty = as.numeric(prct_abv_mean_penalty))%>%
  mutate(policy_enacted = if_else(month_n >= 0, 1, 0))%>%
  mutate(serco_enforced = if_else(
    community_area_number %in% c("6", "7", "8", "24"), 1, 0))%>%
  mutate(serco_enforced = as.numeric(serco_enforced), .keep = "unused")%>%
  mutate(did = policy_enacted*serco_enforced)%>%
  mutate(policy_enacted = as.factor(policy_enacted), .keep="unused")%>%
  mutate(serco_enforced = as.factor(serco_enforced), .keep="unused")%>%
  mutate_at(c('total_commuters'), ~(scale(.) %>% as.vector))%>%
  mutate_at(c('work_at_home'), ~(scale(.) %>% as.vector))%>%
  mutate_at(c('med_inc'), ~(scale(.) %>% as.vector))%>%
  mutate_at(c('park_access'), ~(scale(.) %>% as.vector))%>%
  mutate_at(c('annual_vehicle_miles'), ~(scale(.) %>% as.vector))%>%
  mutate_at(c('white'), ~(scale(.) %>% as.vector))%>%
  mutate_at(c('hisp'), ~(scale(.) %>% as.vector))%>%
  mutate_at(c('black'), ~(scale(.) %>% as.vector))%>%
  mutate_at(c('asian'), ~(scale(.) %>% as.vector))


## Running the DID for the two years around the policy change
#T(-24:24)
didreg = lm(prct_abv_mean_penalty ~

            serco_enforced + policy_enacted + did +

            annual_vehicle_miles + total_commuters + work_at_home + transit+

            white + hisp + black + asian + med_inc,

            data = serco_did)

summary(didreg)
```

```
##
## Call:
## lm(formula = prct_abv_mean_penalty ~ serco_enforced + policy_enacted +
##     did + annual_vehicle_miles + total_commuters + work_at_home +
##     transit + white + hisp + black + asian + med_inc, data = serco_did)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.5550 -0.9497  0.2723  0.8886 17.5684
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)           0.158780   0.029259   5.427 5.75e-08 ***
## serco_enforced1       0.153407   0.041280   3.716 0.000202 ***
## policy_enacted1       0.017618   0.009342   1.886 0.059293 .
## did                  -0.036053   0.012018  -3.000 0.002701 **
## annual_vehicle_miles -0.083709   0.041228  -2.030 0.042317 *
## total_commuters       0.129921   0.036277   3.581 0.000342 ***
## work_at_home         -0.222499   0.056283  -3.953 7.71e-05 ***
## transit              -0.012880   0.001453  -8.865  < 2e-16 ***
## white                -0.005740   0.042723  -0.134 0.893124
## hisp                  0.038935   0.037580   1.036 0.300176
## black                 0.121531   0.021903   5.549 2.89e-08 ***
## asian                -0.046695   0.025477  -1.833 0.066835 .
## med_inc              -0.075094   0.021627  -3.472 0.000516 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9823 on 113497 degrees of freedom
## Multiple R-squared:  0.03469,    Adjusted R-squared:  0.03459
## F-statistic: 339.9 on 12 and 113497 DF,  p-value: < 2.2e-16
```

```
## Testing for difference if the data frame doesn't aggregate tickets to community area level
```

DID of SERCO Enforcement In Other Time Periods DID

```
# T(-12:12)
serco_did_n12_12 <- serco_did %>%
  filter(month_n >= -12 & month_n <= 12)

serco_did_n12_12 = lm(prct_abv_mean_penalty ~

            serco_enforced + policy_enacted + did +

            annual_vehicle_miles + total_commuters + work_at_home + transit+

            white + hisp + black + asian + med_inc,

            data = serco_did_n12_12)

summary(serco_did_n12_12)
```

```
##
## Call:
## lm(formula = prct_abv_mean_penalty ~ serco_enforced + policy_enacted +
##     did + annual_vehicle_miles + total_commuters + work_at_home +
##     transit + white + hisp + black + asian + med_inc, data = serco_did_n12_12)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.5195 -0.9645  0.2897  0.9030 17.6113
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)           0.195168   0.049261   3.962 7.44e-05 ***
## serco_enforced1       0.205892   0.075265   2.736 0.006229 **
## policy_enacted1      -0.022793   0.017947  -1.270 0.204082
## did                   0.020619   0.023918   0.862 0.388666
## annual_vehicle_miles -0.286015   0.093966  -3.044 0.002337 **
## total_commuters       0.291066   0.080070   3.635 0.000278 ***
## work_at_home         -0.501105   0.131136  -3.821 0.000133 ***
## transit              -0.016358   0.002908  -5.626 1.85e-08 ***
## white                -0.216747   0.078362  -2.766 0.005677 **
## hisp                 -0.043647   0.062496  -0.698 0.484938
## black                 0.115772   0.039192   2.954 0.003138 **
## asian                -0.175247   0.055454  -3.160 0.001577 **
## med_inc               0.008098   0.041832   0.194 0.846502
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9845 on 59453 degrees of freedom
## Multiple R-squared:  0.03058,    Adjusted R-squared:  0.03038
## F-statistic: 156.3 on 12 and 59453 DF,  p-value: < 2.2e-16
```

```
# T(-6:6)
serco_did_n6_6 <- serco_did %>%
  filter(month_n >= -6 & month_n <= 6)

serco_did_n6_6 = lm(prct_abv_mean_penalty ~

            serco_enforced + policy_enacted + did +

            annual_vehicle_miles + total_commuters + work_at_home + transit+

            white + hisp + black + asian + med_inc,

            data = serco_did_n6_6 )

summary(serco_did_n6_6)
```

```
##
## Call:
## lm(formula = prct_abv_mean_penalty ~ serco_enforced + policy_enacted +
##     did + annual_vehicle_miles + total_commuters + work_at_home +
##     transit + white + hisp + black + asian + med_inc, data = serco_did_n6_6)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.4438 -0.9168  0.2206  0.8999 17.5065
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)           0.160902   0.040574   3.966 7.33e-05 ***
## serco_enforced1       0.117168   0.055314   2.118   0.0342 *
## policy_enacted1      -0.014597   0.015858  -0.920   0.3573
## did                   0.012902   0.020178   0.639   0.5226
## annual_vehicle_miles -0.016397   0.046651  -0.351   0.7252
## total_commuters       0.068957   0.041617   1.657   0.0975 .
## work_at_home         -0.135879   0.062875  -2.161   0.0307 *
## transit              -0.011722   0.001763  -6.649 2.98e-11 ***
## white                 0.071356   0.054686   1.305   0.1920
## hisp                  0.063193   0.048287   1.309   0.1906
## black                 0.116615   0.027536   4.235 2.29e-05 ***
## asian                 0.010028   0.030146   0.333   0.7394
## med_inc              -0.115722   0.026618  -4.348 1.38e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9804 on 64099 degrees of freedom
## Multiple R-squared:  0.03855,    Adjusted R-squared:  0.03837
## F-statistic: 214.2 on 12 and 64099 DF,  p-value: < 2.2e-16
```

```
# T(-5:5)
serco_did_n5_5 <- serco_did %>%
  filter(month_n >= -5 & month_n <= 5)

serco_did_n5_5 = lm(prct_abv_mean_penalty ~

            serco_enforced + policy_enacted + did +

            annual_vehicle_miles + total_commuters + work_at_home + transit+

            white + hisp + black + asian + med_inc,

            data = serco_did_n5_5)

summary(serco_did_n5_5)
```

```
##
## Call:
## lm(formula = prct_abv_mean_penalty ~ serco_enforced + policy_enacted +
##     did + annual_vehicle_miles + total_commuters + work_at_home +
##     transit + white + hisp + black + asian + med_inc, data = serco_did_n5_5)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.4360 -0.9149  0.2203  0.8939 17.5093
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)           0.168260   0.040088   4.197 2.71e-05 ***
## serco_enforced1       0.094131   0.054580   1.725   0.0846 .
## policy_enacted1      -0.020109   0.014780  -1.361   0.1736
## did                   0.024325   0.018894   1.287   0.1980
## annual_vehicle_miles -0.020243   0.046170  -0.438   0.6611
## total_commuters       0.072663   0.041276   1.760   0.0783 .
## work_at_home         -0.132168   0.062076  -2.129   0.0332 *
## transit              -0.011481   0.001756  -6.537 6.33e-11 ***
## white                 0.057439   0.052925   1.085   0.2778
## hisp                  0.051695   0.046518   1.111   0.2665
## black                 0.110946   0.026464   4.192 2.77e-05 ***
## asian                 0.003709   0.029729   0.125   0.9007
## med_inc              -0.119273   0.026746  -4.460 8.23e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9805 on 62046 degrees of freedom
## Multiple R-squared:  0.03846,    Adjusted R-squared:  0.03828
## F-statistic: 206.8 on 12 and 62046 DF,  p-value: < 2.2e-16
```

```
# T(-4:4)
serco_did_n4_4 <- serco_did %>%
  filter(month_n >= -4 & month_n <= 4)

serco_did_n4_4 = lm(prct_abv_mean_penalty ~

            serco_enforced + policy_enacted + did +

            annual_vehicle_miles + total_commuters + work_at_home + transit+

            white + hisp + black + asian + med_inc,

            data =serco_did_n4_4)

summary(serco_did_n4_4)
```

```
##
## Call:
## lm(formula = prct_abv_mean_penalty ~ serco_enforced + policy_enacted +
##     did + annual_vehicle_miles + total_commuters + work_at_home +
##     transit + white + hisp + black + asian + med_inc, data = serco_did_n4_4)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.4377 -0.9231  0.2454  0.8943 17.5089
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)           0.175889   0.045119   3.898  9.7e-05 ***
## serco_enforced1       0.069204   0.062085   1.115 0.264998
## policy_enacted1      -0.017883   0.014523  -1.231 0.218200
## did                   0.016406   0.018427   0.890 0.373281
## annual_vehicle_miles -0.024066   0.048518  -0.496 0.619881
## total_commuters       0.070842   0.043588   1.625 0.104113
## work_at_home         -0.125436   0.065703  -1.909 0.056247 .
## transit              -0.011061   0.001830  -6.046  1.5e-09 ***
## white                 0.055879   0.057141   0.978 0.328118
## hisp                  0.060908   0.050613   1.203 0.228831
## black                 0.109919   0.028390   3.872 0.000108 ***
## asian                -0.001308   0.031057  -0.042 0.966403
## med_inc              -0.106279   0.028547  -3.723 0.000197 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9809 on 57890 degrees of freedom
## Multiple R-squared:  0.03769,    Adjusted R-squared:  0.03749
## F-statistic: 188.9 on 12 and 57890 DF,  p-value: < 2.2e-16
```

```
# T(-3:3)
serco_did_n3_3 <- serco_did %>%
  filter(month_n >= -3 & month_n <= 3)

serco_did_n3_3 = lm(prct_abv_mean_penalty ~

            serco_enforced + policy_enacted + did +

            annual_vehicle_miles + total_commuters + work_at_home + transit+

            white + hisp + black + asian + med_inc,

            data = serco_did_n3_3)

summary(serco_did_n3_3)
```

```
##
## Call:
## lm(formula = prct_abv_mean_penalty ~ serco_enforced + policy_enacted +
##     did + annual_vehicle_miles + total_commuters + work_at_home +
##     transit + white + hisp + black + asian + med_inc, data = serco_did_n3_3)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.4643 -0.9203  0.2466  0.8937 17.5063
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)           0.153970   0.044904   3.429 0.000607 ***
## serco_enforced1       0.072013   0.061866   1.164 0.244421
## policy_enacted1      -0.010135   0.013955  -0.726 0.467684
## did                   0.006091   0.017772   0.343 0.731807
## annual_vehicle_miles -0.005430   0.048704  -0.111 0.911231
## total_commuters       0.054247   0.043684   1.242 0.214319
## work_at_home         -0.103681   0.065758  -1.577 0.114869
## transit              -0.010061   0.001835  -5.484 4.18e-08 ***
## white                 0.065036   0.054977   1.183 0.236828
## hisp                  0.062671   0.048736   1.286 0.198473
## black                 0.106209   0.027738   3.829 0.000129 ***
## asian                 0.010551   0.031025   0.340 0.733794
## med_inc              -0.108940   0.028504  -3.822 0.000133 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9809 on 58591 degrees of freedom
## Multiple R-squared:  0.0377, Adjusted R-squared:  0.03751
## F-statistic: 191.3 on 12 and 58591 DF,  p-value: < 2.2e-16
```

```
# T(-2:2)
serco_did_n2_2 <- serco_did %>%
  filter(month_n >= -2 & month_n <= 2)

serco_did_n2_2 = lm(prct_abv_mean_penalty ~

            serco_enforced + policy_enacted + did +

            annual_vehicle_miles + total_commuters + work_at_home + transit+

            white + hisp + black + asian + med_inc,

            data = serco_did_n2_2)

summary(serco_did_n2_2)
```

```
##
## Call:
## lm(formula = prct_abv_mean_penalty ~ serco_enforced + policy_enacted +
##     did + annual_vehicle_miles + total_commuters + work_at_home +
##     transit + white + hisp + black + asian + med_inc, data = serco_did_n2_2)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.5742 -0.9601  0.2634  0.8874 17.5586
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)           0.167826   0.044310   3.788 0.000152 ***
## serco_enforced1       0.168109   0.061722   2.724 0.006458 **
## policy_enacted1      -0.005835   0.012724  -0.459 0.646519
## did                  -0.001926   0.016408  -0.117 0.906583
## annual_vehicle_miles -0.113081   0.080164  -1.411 0.158364
## total_commuters       0.142893   0.067116   2.129 0.033253 *
## work_at_home         -0.262887   0.107719  -2.440 0.014670 *
## transit              -0.013832   0.002516  -5.496 3.89e-08 ***
## white                 0.049770   0.063786   0.780 0.435236
## hisp                  0.097244   0.048088   2.022 0.043161 *
## black                 0.161132   0.031672   5.087 3.64e-07 ***
## asian                -0.039617   0.048830  -0.811 0.417180
## med_inc              -0.076760   0.038004  -2.020 0.043409 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9823 on 60267 degrees of freedom
## Multiple R-squared:  0.03494,	Adjusted R-squared:  0.03475
## F-statistic: 181.8 on 12 and 60267 DF,  p-value: < 2.2e-16
```

```
# T(-1:1)
serco_did_n1_1 <- serco_did %>%
  filter(month_n >= -2 & month_n <= 1)

serco_did_n1_1 = lm(prct_abv_mean_penalty ~

            serco_enforced + policy_enacted + did +

            annual_vehicle_miles + total_commuters + work_at_home + transit+

            white + hisp + black + asian + med_inc,

            data = serco_did_n1_1)

summary(serco_did_n1_1)
```

```
##
## Call:
## lm(formula = prct_abv_mean_penalty ~ serco_enforced + policy_enacted +
##     did + annual_vehicle_miles + total_commuters + work_at_home +
##     transit + white + hisp + black + asian + med_inc, data = serco_did_n1_1)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.5326 -0.9512  0.2888  0.9072 17.6167
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)           0.248603   0.064946   3.828 0.000130 ***
## serco_enforced1       0.183904   0.096076   1.914 0.055609 .
## policy_enacted1      -0.039629   0.025895  -1.530 0.125941
## did                   0.047994   0.034930   1.374 0.169448
## annual_vehicle_miles -0.371727   0.118880  -3.127 0.001768 **
## total_commuters       0.376813   0.100992   3.731 0.000191 ***
## work_at_home         -0.596739   0.164156  -3.635 0.000278 ***
## transit              -0.018505   0.003724  -4.969 6.76e-07 ***
## white                -0.109598   0.094415  -1.161 0.245724
## hisp                  0.127870   0.077603   1.648 0.099415 .
## black                 0.218665   0.050171   4.358 1.31e-05 ***
## asian                -0.192540   0.070810  -2.719 0.006549 **
## med_inc               0.032824   0.054247   0.605 0.545133
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9834 on 33103 degrees of freedom
## Multiple R-squared:  0.03289,	Adjusted R-squared:  0.03254
## F-statistic:  93.8 on 12 and 33103 DF,  p-value: < 2.2e-16
```

DID of Relationship Between SERCO and City Ticketing w/ Inflection Date

```
## DID units and Neighborhoods
## Creating the Serco Data Frame with the selected experiment and control groups
# First to select the relevant variables to make the data set more tidy
# Outcome Variables: total_payments

serco_tidy_df <- chi_tickets %>%
    filter(community_area_name == "LAKE VIEW"|
         community_area_name == "NEAR NORTH SIDE"|
         community_area_name == "WEST TOWN"|
         community_area_name == "LINCOLN PARK"|
         community_area_name == "BRIGHTON PARK"|
         community_area_name == "NEAR WEST SIDE"|
         community_area_name == "ROGERS PARK"|
         community_area_name == "PORTAGE PARK")%>%
    filter(year %in% (2009:2014))%>%
  filter(total_payments >= 0)%>%
  mutate(total_penalties = if_else(current_amount_due >= 0,
          total_payments + current_amount_due - fine_level1_amount,
          total_payments - fine_level1_amount))%>%
  filter(total_penalties >= 0)%>%
  mutate(prct_penalty = total_penalties/fine_level1_amount)%>%
  select(-current_amount_due,
         -issue_date,
         -total_payments,
         -ticket_number,
         -fine_level1_amount,
         -fine_level2_amount)%>%
  mutate(community_area_number = as.character(community_area_number))%>%
  mutate(month_n = case_when(month == 9 & year == 2009 ~ "-24",
                             month == 10 & year == 2009 ~ "-23",
                             month == 11 & year == 2009 ~"-22",
                             month == 12 & year == 2009 ~ "-21",
                             month == 1 & year == 2010 ~ "-20",
                             month == 2 & year == 2010 ~ "-19",
                             month == 3 & year == 2010 ~ "-18",
                             month == 4 & year == 2010 ~ "-17",
                             month == 5 & year == 2010 ~ "-16",
                             month == 6 & year == 2010 ~ "-15",
                             month == 7 & year == 2010 ~ "-14",
                             month == 8 & year == 2010 ~ "-13",
                             month == 9 & year == 2010 ~ "-12",
                             month == 10 & year == 2010 ~ "-11",
                             month == 11 & year == 2010 ~ "-10",
                             month == 12 & year == 2010 ~ "-9",
                             month == 1 & year == 2011 ~ "-8",
                             month == 2 & year == 2011 ~ "-6",
                             month == 3 & year == 2011 ~ "-5",
                             month == 4 & year == 2011 ~ "-4",
                             month == 5 & year == 2011 ~ "-3",
                             month == 6 & year == 2011 ~ "-2",
                             month == 7 & year == 2011 ~ "-1",
                             month == 8 & year == 2011 ~ "0",
                             month == 9 & year == 2011 ~ "1",
                             month == 10 & year == 2011 ~ "2",
                             month == 11 & year == 2011 ~ "3",
                             month == 12 & year == 2011 ~ "4",
                             month == 1 & year == 2012 ~ "5",
                             month == 2 & year == 2012 ~ "6",
                             month == 3 & year == 2012 ~ "7",
                             month == 4 & year == 2012 ~ "8",
                             month == 5 & year == 2012 ~ "9",
                             month == 6 & year == 2012 ~ "10",
                             month == 7 & year == 2012 ~ "11",
                             month == 8 & year == 2012 ~ "12",
                             month == 9 & year == 2012 ~ "13",
                             month == 10 & year == 2012 ~ "14",
                             month == 11 & year == 2012 ~ "15",
                             month == 12 & year == 2012 ~ "16",
                             month == 1 & year == 2013 ~ "17",
                             month == 2 & year == 2013 ~ "17",
                             month == 3 & year == 2013 ~ "18",
                             month == 4 & year == 2013 ~ "19",
```

```
                             month == 5 & year == 2013 ~ "20",
                             month == 6 & year == 2013 ~ "21",
                             month == 7 & year == 2013 ~ "22",
                             month == 8 & year == 2013 ~ "23",
                             month == 9 & year == 2013 ~ "24"))%>%
  filter(month_n != "NA")

serco_did <- serco_tidy_df %>%
  group_by(month_n)%>%
  mutate_at(c('prct_penalty'), ~(scale(.) %>% as.vector))%>%
  rename(prct_abv_mean_penalty = "prct_penalty")%>%
  mutate(prct_abv_mean_penalty = as.numeric(prct_abv_mean_penalty))%>%
  mutate(policy_enacted = if_else(month_n >= 0, 1, 0))%>%
  mutate(serco_enforced = if_else(
    community_area_number %in% c("6", "7", "8", "24"), 1, 0))%>%
  mutate(serco_enforced = as.numeric(serco_enforced), .keep = "unused")%>%
  mutate(did = policy_enacted*serco_enforced)%>%
  mutate(policy_enacted = as.factor(policy_enacted), .keep="unused")%>%
  mutate(serco_enforced = as.factor(serco_enforced), .keep="unused")%>%
  mutate_at(c('total_commuters'), ~(scale(.) %>% as.vector))%>%
  mutate_at(c('work_at_home'), ~(scale(.) %>% as.vector))%>%
  mutate_at(c('med_inc'), ~(scale(.) %>% as.vector))%>%
  mutate_at(c('park_access'), ~(scale(.) %>% as.vector))%>%
  mutate_at(c('annual_vehicle_miles'), ~(scale(.) %>% as.vector))%>%
  mutate_at(c('white'), ~(scale(.) %>% as.vector))%>%
  mutate_at(c('hisp'), ~(scale(.) %>% as.vector))%>%
  mutate_at(c('black'), ~(scale(.) %>% as.vector))%>%
  mutate_at(c('asian'), ~(scale(.) %>% as.vector))


## Running the DID for the two years around the policy change
#T(-24:24)
didreg = lm(prct_abv_mean_penalty ~

            serco_enforced + policy_enacted + did +

            annual_vehicle_miles + total_commuters + work_at_home + transit+

            white + hisp + black + asian + med_inc,

            data = serco_did)

summary(didreg)
```

```
##
## Call:
## lm(formula = prct_abv_mean_penalty ~ serco_enforced + policy_enacted +
##     did + annual_vehicle_miles + total_commuters + work_at_home +
##     transit + white + hisp + black + asian + med_inc, data = serco_did)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.5502 -0.9491  0.2708  0.8920 17.5840
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)           0.178641   0.032209   5.546 2.93e-08 ***
## serco_enforced1       0.214768   0.045189   4.753 2.01e-06 ***
## policy_enacted1       0.012990   0.009779   1.328  0.18404
## did                  -0.035324   0.012555  -2.814  0.00490 **
## annual_vehicle_miles -0.180980   0.058001  -3.120  0.00181 **
## total_commuters       0.206651   0.049329   4.189 2.80e-05 ***
## work_at_home         -0.359351   0.078651  -4.569 4.91e-06 ***
## transit              -0.015676   0.001844  -8.501  < 2e-16 ***
## white                -0.028370   0.048380  -0.586  0.55760
## hisp                  0.070823   0.038541   1.838  0.06612 .
## black                 0.162139   0.024609   6.589 4.46e-11 ***
## asian                -0.098503   0.035030  -2.812  0.00492 **
## med_inc              -0.043561   0.027312  -1.595  0.11073
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9827 on 109005 degrees of freedom
## Multiple R-squared:  0.03408,	Adjusted R-squared:  0.03398
## F-statistic: 320.5 on 12 and 109005 DF,  p-value: < 2.2e-16
```

DID of Other Time Periods w/ Inflection Date

```
# T(-12:12)
serco_did_n12_12 <- serco_did %>%
  filter(month_n >= -12 & month_n <= 12)

serco_did_n12_12 = lm(prct_abv_mean_penalty ~

            serco_enforced + policy_enacted + did +

            annual_vehicle_miles + park_access + total_commuters + work_at_home +

            white + hisp + black + asian + med_inc, data = serco_did_n12_12)

summary(serco_did_n12_12)
```

```
##
## Call:
## lm(formula = prct_abv_mean_penalty ~ serco_enforced + policy_enacted +
##     did + annual_vehicle_miles + park_access + total_commuters +
##     work_at_home + white + hisp + black + asian + med_inc, data = serco_did_n12_12)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.5010 -0.9568  0.2662  0.8981 17.5968
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)           0.02859    0.03412   0.838 0.402137
## serco_enforced1      -0.04979    0.05864  -0.849 0.395783
## policy_enacted1       0.04795    0.01591   3.014 0.002582 **
## did                  -0.06858    0.01895  -3.618 0.000297 ***
## annual_vehicle_miles -0.17793    0.07728  -2.302 0.021320 *
## park_access          -0.11166    0.01688  -6.615 3.75e-11 ***
## total_commuters       0.09988    0.04970   2.010 0.044469 *
## work_at_home         -0.31127    0.10129  -3.073 0.002119 **
## white                -0.16887    0.07472  -2.260 0.023813 *
## hisp                  0.03968    0.06648   0.597 0.550572
## black                 0.15892    0.04254   3.735 0.000188 ***
## asian                -0.22220    0.06062  -3.665 0.000247 ***
## med_inc               0.21443    0.06908   3.104 0.001911 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9829 on 51320 degrees of freedom
## Multiple R-squared:  0.03373,	Adjusted R-squared:  0.03351
## F-statistic: 149.3 on 12 and 51320 DF,  p-value: < 2.2e-16
```

```
# T(-6:6)
serco_did_n6_6 <- serco_did %>%
  filter(month_n >= -6 & month_n <= 6)

serco_did_n6_6 = lm(prct_abv_mean_penalty ~

            serco_enforced + policy_enacted + did +

            annual_vehicle_miles + park_access + total_commuters + work_at_home +

            white + hisp + black + asian + med_inc,

            data = serco_did_n6_6 )

summary(serco_did_n6_6)
```

```
##
## Call:
## lm(formula = prct_abv_mean_penalty ~ serco_enforced + policy_enacted +
##     did + annual_vehicle_miles + park_access + total_commuters +
##     work_at_home + white + hisp + black + asian + med_inc, data = serco_did_n6_6)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.4949 -0.9331  0.2521  0.9047  8.9440
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)          -0.028255   0.033021  -0.856   0.3922
## serco_enforced1       0.051790   0.054781   0.945   0.3445
## policy_enacted1       0.035736   0.022737   1.572   0.1160
## did                  -0.064091   0.030943  -2.071   0.0383 *
## annual_vehicle_miles -0.026205   0.067996  -0.385   0.6999
## park_access          -0.082899   0.014408  -5.754 8.77e-09 ***
## total_commuters      -0.009978   0.042778  -0.233   0.8156
## work_at_home         -0.150034   0.086984  -1.725   0.0846 .
## white                 0.013306   0.058219   0.229   0.8192
## hisp                  0.079014   0.047666   1.658   0.0974 .
## black                 0.142750   0.033059   4.318 1.58e-05 ***
## asian                -0.091073   0.053463  -1.703   0.0885 .
## med_inc               0.078526   0.060093   1.307   0.1913
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9813 on 66323 degrees of freedom
## Multiple R-squared:  0.03692,    Adjusted R-squared:  0.03674
## F-statistic: 211.9 on 12 and 66323 DF,  p-value: < 2.2e-16
```

```
# T(-5:5)
serco_did_n5_5 <- serco_did %>%
  filter(month_n >= -5 & month_n <= 5)

serco_did_n5_5 = lm(prct_abv_mean_penalty ~

            serco_enforced + policy_enacted + did +

            annual_vehicle_miles + park_access + total_commuters + work_at_home +

            white + hisp + black + asian + med_inc,

            data = serco_did_n5_5)

summary(serco_did_n5_5)
```

```
##
## Call:
## lm(formula = prct_abv_mean_penalty ~ serco_enforced + policy_enacted +
##     did + annual_vehicle_miles + park_access + total_commuters +
##     work_at_home + white + hisp + black + asian + med_inc, data = serco_did_n5_5)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.4898 -0.9367  0.2523  0.9019  5.1895
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)          -0.02846    0.03107  -0.916  0.35968
## serco_enforced1       0.05272    0.05315   0.992  0.32118
## policy_enacted1       0.04058    0.01963   2.067  0.03870 *
## did                  -0.07256    0.02641  -2.747  0.00601 **
## annual_vehicle_miles -0.01103    0.06731  -0.164  0.86986
## park_access          -0.08427    0.01429  -5.896 3.73e-09 ***
## total_commuters      -0.02151    0.04264  -0.505  0.61388
## work_at_home         -0.13057    0.08615  -1.516  0.12963
## white                 0.01974    0.05836   0.338  0.73516
## hisp                  0.07445    0.04786   1.556  0.11980
## black                 0.14089    0.03295   4.276 1.91e-05 ***
## asian                -0.08590    0.05294  -1.623  0.10466
## med_inc               0.07555    0.05983   1.263  0.20669
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9811 on 66557 degrees of freedom
## Multiple R-squared:  0.03719,    Adjusted R-squared:  0.03702
## F-statistic: 214.3 on 12 and 66557 DF,  p-value: < 2.2e-16
```

```
# T(-4:4)
serco_did_n4_4 <- serco_did %>%
  filter(month_n >= -4 & month_n <= 4)

serco_did_n4_4 = lm(prct_abv_mean_penalty ~

            serco_enforced + policy_enacted + did +

            annual_vehicle_miles + park_access + total_commuters + work_at_home +

            white + hisp + black + asian + med_inc,

            data = serco_did_n4_4)

summary(serco_did_n4_4)
```

```
##
## Call:
## lm(formula = prct_abv_mean_penalty ~ serco_enforced + policy_enacted +
##     did + annual_vehicle_miles + park_access + total_commuters +
##     work_at_home + white + hisp + black + asian + med_inc, data = serco_did_n4_4)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.4842 -0.9369  0.2476  0.8921  5.1930
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)          -0.01728    0.03035  -0.569 0.569042
## serco_enforced1       0.03261    0.05344   0.610 0.541656
## policy_enacted1       0.03839    0.01832   2.096 0.036074 *
## did                  -0.06698    0.02443  -2.742 0.006108 **
## annual_vehicle_miles -0.01647    0.06693  -0.246 0.805606
## park_access          -0.08502    0.01424  -5.970 2.38e-09 ***
## total_commuters      -0.01664    0.04236  -0.393 0.694478
## work_at_home         -0.12825    0.08569  -1.497 0.134460
## white                -0.01980    0.05714  -0.347 0.728950
## hisp                  0.04762    0.04849   0.982 0.326093
## black                 0.12642    0.03344   3.781 0.000156 ***
## asian                -0.09484    0.05249  -1.807 0.070795 .
## med_inc               0.08174    0.05944   1.375 0.169102
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9808 on 66245 degrees of freedom
## Multiple R-squared:  0.03793,	Adjusted R-squared:  0.03776
## F-statistic: 217.7 on 12 and 66245 DF,  p-value: < 2.2e-16
```

```
# T(-3:3)
serco_did_n3_3 <- serco_did %>%
  filter(month_n >= -3 & month_n <= 3)

serco_did_n3_3 = lm(prct_abv_mean_penalty ~

            serco_enforced + policy_enacted + did +

            annual_vehicle_miles + park_access + total_commuters + work_at_home +

            white + hisp + black + asian + med_inc,

            data = serco_did_n3_3)

summary(serco_did_n3_3)
```

```
##
## Call:
## lm(formula = prct_abv_mean_penalty ~ serco_enforced + policy_enacted +
##     did + annual_vehicle_miles + park_access + total_commuters +
##     work_at_home + white + hisp + black + asian + med_inc, data = serco_did_n3_3)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.4965 -0.9371  0.2458  0.8874 17.5343
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)          -0.008469   0.030115  -0.281  0.77855
## serco_enforced1       0.016131   0.054022   0.299  0.76525
## policy_enacted1       0.037853   0.017381   2.178  0.02942 *
## did                  -0.063730   0.022875  -2.786  0.00534 **
## annual_vehicle_miles -0.059999   0.065882  -0.911  0.36246
## park_access          -0.096947   0.014148  -6.852 7.32e-12 ***
## total_commuters       0.012398   0.041800   0.297  0.76677
## work_at_home         -0.178895   0.084518  -2.117  0.03429 *
## white                -0.064172   0.056466  -1.136  0.25576
## hisp                  0.047403   0.048470   0.978  0.32809
## black                 0.132027   0.033353   3.958 7.55e-05 ***
## asian                -0.132961   0.051836  -2.565  0.01032 *
## med_inc               0.122061   0.058705   2.079  0.03760 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9804 on 65905 degrees of freedom
## Multiple R-squared:  0.03864,	Adjusted R-squared:  0.03846
## F-statistic: 220.7 on 12 and 65905 DF,  p-value: < 2.2e-16
```

```
# T(-2:2)
serco_did_n2_2 <- serco_did %>%
  filter(month_n >= -2 & month_n <= 2)

serco_did_n2_2 = lm(prct_abv_mean_penalty ~

            serco_enforced + policy_enacted + did +

            annual_vehicle_miles + park_access + total_commuters + work_at_home +

            white + hisp + black + asian + med_inc,

            data = serco_did_n2_2)

summary(serco_did_n2_2)
```

```
##
## Call:
## lm(formula = prct_abv_mean_penalty ~ serco_enforced + policy_enacted +
##     did + annual_vehicle_miles + park_access + total_commuters +
##     work_at_home + white + hisp + black + asian + med_inc, data = serco_did_n2_2)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.4616 -0.9426  0.2674  0.8915 17.5404
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)          0.0009714  0.0331719   0.029 0.976638
## serco_enforced1     -0.0018470  0.0607373  -0.030 0.975740
## policy_enacted1      0.0277231  0.0164876   1.681 0.092682 .
## did                 -0.0454964  0.0216010  -2.106 0.035191 *
## annual_vehicle_miles -0.1690210  0.0800268  -2.112 0.034687 *
## park_access         -0.1073331  0.0168460  -6.371 1.89e-10 ***
## total_commuters      0.1099626  0.0511824   2.148 0.031683 *
## work_at_home        -0.3156742  0.1044152  -3.023 0.002502 **
## white               -0.1585548  0.0690641  -2.296 0.021694 *
## hisp                 0.0730294  0.0696599   1.048 0.294473
## black                0.1693392  0.0452140   3.745 0.000180 ***
## asian               -0.2071010  0.0608966  -3.401 0.000672 ***
## med_inc              0.2010010  0.0713155   2.818 0.004827 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9808 on 49673 degrees of freedom
## Multiple R-squared:  0.03788,	Adjusted R-squared:  0.03765
## F-statistic:   163 on 12 and 49673 DF,  p-value: < 2.2e-16
```

```
# T(-1:1)
serco_did_n1_1 <- serco_did %>%
  filter(month_n >= -2 & month_n <= 1)

serco_did_n1_1 = lm(prct_abv_mean_penalty ~

            serco_enforced + policy_enacted + did +

            annual_vehicle_miles + park_access + total_commuters + work_at_home +

            white + hisp + black + asian + med_inc,

            data = serco_did_n1_1)

summary(serco_did_n1_1)
```

```
##
## Call:
## lm(formula = prct_abv_mean_penalty ~ serco_enforced + policy_enacted +
##     did + annual_vehicle_miles + park_access + total_commuters +
##     work_at_home + white + hisp + black + asian + med_inc, data = serco_did_n1_1)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.4217 -0.9851  0.2837  0.8895 17.6936
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)           0.007844   0.086219   0.091 0.927515
## serco_enforced1      -0.014914   0.163049  -0.091 0.927122
## policy_enacted1       0.074757   0.026541   2.817 0.004858 **
## did                  -0.122455   0.030564  -4.007 6.19e-05 ***
## annual_vehicle_miles -0.075970   0.147380  -0.515 0.606229
## park_access          -0.075216   0.029227  -2.574 0.010074 *
## total_commuters       0.057116   0.091949   0.621 0.534494
## work_at_home         -0.178206   0.210243  -0.848 0.396661
## white                -0.448066   0.128875  -3.477 0.000509 ***
## hisp                 -0.349730   0.135673  -2.578 0.009952 **
## black                -0.047961   0.086741  -0.553 0.580325
## asian                -0.188200   0.109403  -1.720 0.085404 .
## med_inc               0.078943   0.128768   0.613 0.539840
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9819 on 19381 degrees of freedom
## Multiple R-squared:  0.03601,	Adjusted R-squared:  0.03541
## F-statistic: 60.33 on 12 and 19381 DF,  p-value: < 2.2e-16
```