Red-Light and Speed Cameras: Analyzing the Equity and Efficacy of Chicago's Automated Camera Enforcement Program

Final Report

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Report to the City of Chicago Mayor's Office and Department of Transportation

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01 INTRODUCTION

This is a watershed moment in which public demands for roadway safety intersect with public outcry for municipal fine and fee reform.[1] This is evident in an unprecedented alliance between the Vision Zero Network, principally concerned with improving road safety and eliminating traffic fatalities, and the Fines and Fees Justice Center. These advocacy organizations agree that monetary sanctions for all manner of traffic infractions do not necessarily make our roads safer. Instead, fines, fees, forfeitures, and other imposed costs disproportionately harm poor people, particularly in Black and Latinx communities, thereby distorting the justice system and thwarting regulatory compliance.

Debates about the efficacy of automated enforcement of red-light and speed cameras can be contentious, and findings can be ambiguous, but the empirical evidence suggests that roadways are typically safer once cameras are installed. Numerous studies find that the automated enforcement cameras reduce the overall number of collisions as well as the severity of vehicular injuries.[2] Nevertheless, as of July 2021, 11 states have prohibited or restricted cameras.[3] According to the Insurance Institute for Highway Safety, the number of municipalities using red-light cameras has declined from 533 in 2012 to 345 by 2020.[4]

Although public sentiment is generally more favorable toward speed cameras, implementation of speed camera programs has declined, with some jurisdictions restricting speed cameras to specific zones. For example, Pennsylvania recently enacted an initiative, Automated Work Zone Speed Enforcement, which allows speed enforcement cameras in active construction zones on the Turnpike, interstates, and highway system. Drivers caught traveling 11 mph or more over the speed limit are mailed a ticket for $75 for the first violation.[5] The constitutionality of automated enforcement laws are being challenged in numerous states. Jurisdictions that have recently discontinued camera enforcement usage, such as Texas and New Jersey, cite dubious efficacy of automated cameras, challenges enforcing violations, expense of maintaining the program, and, most frequently, community opposition to inadequate transparency in the system.[6]

Racial disparities in municipal ticketing and the regressivity of monetary sanctions are robust literatures.[7] Camera enforcement technologies are frequently excluded from the analyses, although automated enforcement typically yields the largest volume of tickets annually. Traffic enforcement cameras have attracted unlikely support from advocates of police reform because cameras, presumably, offer a race-neutral alternative to police enforcement of traffic infractions. Proponents emphasize dual concerns -- racially disproportionate stops and the risk of violent encounters with police particularly for Black drivers – mitigated by traffic enforcement cameras.[8] Automation provides apparent advantages to police enforcement, but it does not eliminate racial and economic inequities. The spatial location of cameras, the volume of automated tickets issued, and the structure of ticket fines, fees and forfeitures can reinforce and further racial and economic inequities.

The *purpose of this study* is to analyze the City of Chicago's automated red-light and speed camera enforcement program given the dual concerns of traffic camera effectiveness for improving roadway safety and social and economic equity impacts. This study contributes to the Chicago Department of Transportation's (CDOT) effort to routinely evaluate the efficacy, functionality, distributive effects of red-light and speed cameras, known as the City of Chicago Automated Enforcement Program.

This study of Chicago's Automated Enforcement Program tackles three empirical questions around which this report is organized. *First*, what are social and spatial distributional effects of red-light and speed camera tickets for city households? To address this concern, data are analyzed at both the camera-level and the neighborhood/census tract-level. *Second*, what are economic effects of camera ticket fines and fees, and are effects equitably distributed across Chicago neighborhoods and households? To explore this question, measures of economic burden are used to compare neighborhoods and households. *Third*, how effective are Chicago's speed cameras for improving safety? The incidence and severity of crashes at more than 100 speed cameras across the city are analyzed. Findings from all three areas of inquiry inform our recommendations to the City of Chicago Mayor's Office and City Departments responsible for administering automated enforcement policies, monitoring camera effectiveness, and structuring penalties.

Before turning to the empirical chapters, the next section briefly describes the City's Automated Enforcement Program, followed by a description of the camera ticket data used in this study. Each of the three research aims employs a distinct methodology and data sources, which are detailed within respective empirical chapters. Finally, *Appendix A-C* contains regression output, site-level crash counts, and other technical documentation that corresponds with the three empirical chapters.

02 CHICAGO'S AUTOMATED ENFORCEMENT CAMERAS

The City of Chicago has one of the largest and longest operating automated traffic enforcement systems in the country. Chicago's Automated Enforcement Program began under Mayor Richard M. Daley in July 2003 with the passing of a city ordinance authorizing red-light cameras. By the end of the year the first red-light cameras were installed and activated at two intersections – N. Western Ave. & Peterson Ave. and S. Western Ave. & Garfield Blvd. The number and dispersion of red-light cameras across the city consistently increased until reaching a peak of nearly 400 cameras in 2013. Since then, the city's usage of automated red-light cameras has declined to approximately 300 operating at 149 intersections by 2020.

In 2012, the State of Illinois permitted the City of Chicago to install speed enforcement cameras in a maximum of 20% of all eligible Child Safety Zones, which are 1/8th of mile buffers around schools and parks. Automated speed enforcement camera program officially began in August 2013. As of 2019, there were 161 speed cameras operating in 68 of the city's nearly1,500 Safety Zones. Approximately 87% of speed cameras were installed during the first two years of the program.

In addition to cameras, the city has implemented a variety of traffic calming mechanisms to enhance pedestrian safety including better road markings, radar speed signs, pedestrian refuge islands, speed humps, road diets or lane reduction, and more.[9] However, these and other roadway safety tools are not equally distributed across city neighborhoods.

The Automated Traffic Enforcement Program is officially administered and managed by CDOT. The city contracts private vendors to install, calibrate, monitor, and maintain requisite hardware and software for tracking vehicle motion and capturing infractions with high-resolution digital photographs and video. For the first ten years of the red-light camera program, the City's vendor was Redflex Traffic Systems. In October 2013, the contract was transferred to the current vendor, Conduent State and Local Solutions. American Traffic Solutions (rebranded as Verra Mobility) has been the speed camera vendor since the program's inception.

Illinois State Law mandates manual review of all red-light and speed camera enforcement of all vehicular triggering of camera sensors, also referred to as "events." The vendors review images and video for all events and make the initial determination as to whether a valid vehicular infraction has occurred. Prima facie evidence of violations is transferred to the Department of Finance for a final determination and enforcement. The Department of Finance mails violation notices to the address of the registered vehicle owner. In 2019, just 31% of red-light camera events and 28% of speed camera events were determined to be enforceable violations.[10]

03 CAMERA TICKET DATA

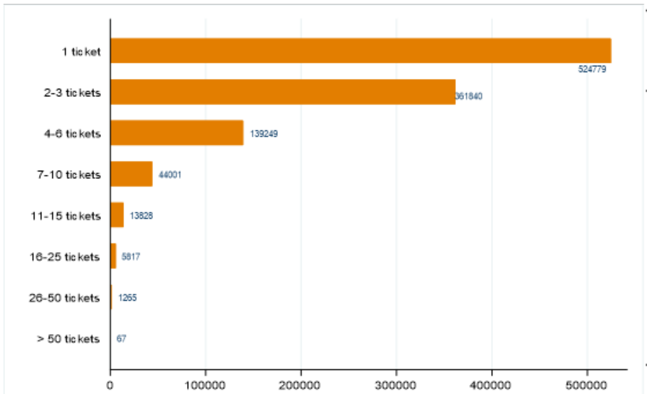
This study draws on proprietary red-light and speed camera and ticket data obtained from the Chicago Department of Finance for the years 2016-2019.

We focus on 438 cameras (289 red-light and 149 speed) operational throughout the study period. Over four years, these cameras generated 5,735,680 enforceable violation notices or "tickets" mailed to vehicle owners. As shown in *Table 1*, of the five million camera tickets issued, 3,013,517 tickets were issued to Chicago residents, owners of vehicles registered within the City of Chicago. This study analyzes 2,707,216 red-light and speed camera tickets to Chicago households because we were able to geocode these tickets based on the addresses provided. We excluded from analyses about 14,000 red-light and speed camera tickets that we determined were issued to vehicles registered to identifiable institutions, such as police stations, public facilities, airports, and car dealerships, among other institutions.

Table 1 *Number of automated camera tickets issued to Chicago residents, and tickets analyzed in this study*

Camera Ticket Description (2016-2019)	Tickets Issued	Tickets Analyzed	
Red-light Tickets	1,151,757	1,021,891	38%
Speed Tickets ≥11mph over	954,791	878,684	32%
Speed Tickets 10 mph over limit	284,916	263,367	10%
Speed warnings	622,053	543,274	20%
	3,013,517	2,707,216	100%

There is not a reliable measure of the number of Chicago households that received camera tickets. The vehicle-level variables likely inflate the number of households. However, the camera ticket dataset includes a vehicle-level variable "Notice Number" that is useful estimate of drivers. Notice Number can be tracked over time and across address changes, thus it serves as a proxy for vehicle license plate for determining camera ticket frequency by vehicle (*Figure 1*). Further analysis is needed to exploit driver-level patterns. However, ticket frequencies in *Table 1* might inform high-level policy decisions regarding vehicles that accumulate multiple tickets per year, although the driver is unknown. Over four years, 1,090,847 vehicles registered in Chicago were issued 2,707,206 red-light and speed camera tickets. It is worth noting that 48% of ticketed vehicles received just one violation. This includes one Speed Warning ticket. An additional 33% received 2-3 violations. This suggests that a relatively small proportion of registered ticketed vehicles accumulated what would amount to two of more tickets per year over four years. As we discuss later, skewedness in vehicle ticketing warrants considering the number of infractions as one of the criteria for reforming the city's system of fines and fees.



Ticket Freq. by Vehicle, 2016-2019

	vehicles	%	cum.
1 ticket	524,779	48.11	48.11
2-3 tickets	361,840	33.17	81.28
4-6 tickets	139,249	12.77	94.04
7-10 tickets	44,002	4.03	98.08
11-15 tickets	13,828	1.27	99.34
16-25 tickets	5,817	0.53	99.88
26-50 tickets	1,265	0.12	99.99
> 50 tickets	67	0.01	100
Total	1,090,847		

Figure 1 *Frequency of camera tickets over four years by vehicle*

Camera Ticket Fine Levels

Fine levels are presented in Table 2. In compliance with State statute and municipal code, owners of registered vehicles are fined $100 for all camera enforced red-light violations, $100 for camera speed violations equal to or more than 11 mph over the posted limit, and $35 for speeding 6-10 mph over the limit, although tickets were only sent when driving 10 mph over the limit. This policy changed in 2021; $35 tickets are now issued for speed violations 6-10 mph. First time offenders of camera enforced speed regulations are issued a Warning ticket, which has no monetary fine. Between 2016 and 2019, 20% of all speed camera tickets (or 30% of all camera tickets) result in Speed Warning tickets. Understanding the effectiveness of Speed Warning tickets for deterring subsequent speed violations is an area for further study.

Table 2 *Fine levels for camera ticket violations*

Camera Ticket Fines (2016-2019)	Fine Level
Red-light Tickets	$100
Speed Tickets $\geq$11mph over	$100
Speed Tickets 10 mph over limit	$35
Speed warnings	$0

Camera Ticket Attributes

The automated enforcement camera dataset obtained from the Chicago Department of Finance included the attributes listed in *Table 3* sans fees which was derived by the authors. The three empirical chapters include data and methods sections where the specific data used in analyses are described in more detail.

Table 3 *Camera Ticket dataset variables*

Chicago Camera Ticket Data Attributes of Interest	
Notice Number	Unique identifier assigned to vehicles
Address	Address of register vehicle
Year	Year ticket was issued
Camera ID	Unique identifier for Red-light and Speed cameras
Camera Location	Street location for cameras, date installed or decommissioned
Violation Description	Red-Light, Speed 11+, Speed 6-10, Warning
Ticket Queue	Paid, Backruptcy, Court, Dismissed, Notice, Warning
Fine Level	Dollar value of initial fine per ticket
Total Payments	Dollar value received by the city, as of December 2019
Current Amount Due	Dollar value unpaid, as of December 2019
Fees	Total Payments minus Fine Level, Dollar value (researcher deduced)
Booted	Vehicle immobalized by the city (Y/N)
Towed	Vehicle towed to car pound (Y/N)
Collections	Ticket went to a collection agency for unpaid balance (Y/N)
Additional Datasets	
CDOF	Red-light and Speed Camera Tickets and Cameras
CDOT	Camera traffic volume
IDOT	Annual Average Daily Traffic
IDOT	IL Road Crash Data
Wells Associates/D&B	National Establishment Time Series
Chicago Data Portal	Crime statistics
Chicago Data Portal	Ride-hailing trips (drivers)
US Census	American Community Survey, 5-year 2015-2019
US Census	Longitudinal Employer-Household Dynamics

04 SPATIAL AND SOCIAL DISTRIBUTION OF TICKETS

Introduction

This chapter examines ticketing patterns across Chicago. For both red-light and speed cameras, rates of ticketing per household at the census tract level as well as rates of ticketing per vehicle at the camera level are examined.

Between 2016-2019, there were a total of 971,235 red light tickets and 1,634,521 speeding tickets issued to households in the city that we were able to geocode based on the addresses provided. At the city level, this is equivalent to 0.23 red-light tickets per household per year and 0.38 speeding tickets per household per year. However, there are significant differences across the city when ticketing levels are examined at the census tract basis. Rates of red-light tickets range from 0.04-0.71 tickets per household per year, and speed tickets range from 0.07-0.94 tickets per household per year. Census tracts that are on the higher end of these ranges are predominantly majority Black areas followed by majority Latinx/Hispanic areas.

Figure 1 shows a box and whisker plot of the distribution of ticketing rates by majority race/ethnicity in city of Chicago. *Figures 2* shows the spatial distribution of tickets per household for red-light cameras and speed cameras across the city. Both figures show the intensity of ticketing for red-light and speed cameras are highest in the predominantly Black and Latinx/Hispanic areas of the city.

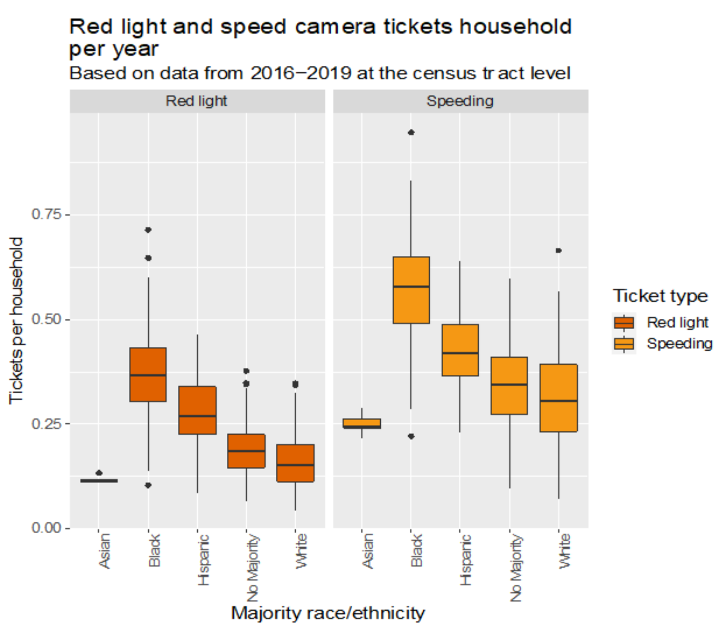


Figure 1 *The Distribution of automated tickets per household per year by race/ethnicity in Chicago (2016-2019)*

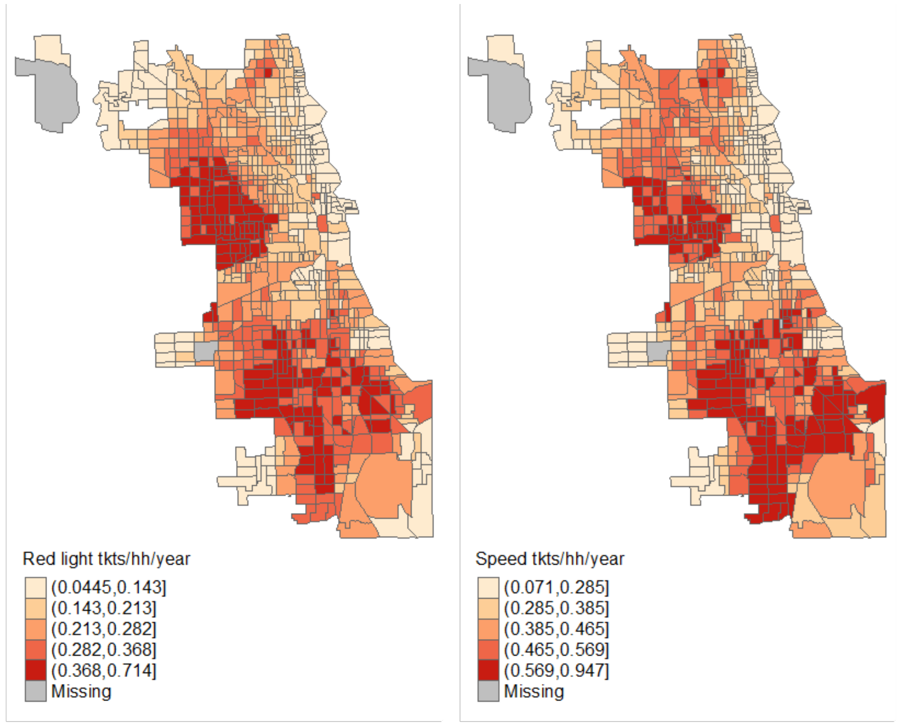


Figure 2 *The spatial pattern of ticketing per household per year (2016-2019)*

We use households as the denominator in this analysis because the tickets are issued to specific addresses. Using the total number of vehicles in a census tract as the denominator also leads to similar patterns. In *Figure 2*, areas showing as missing in the maps have no households reported and correspond to the O'Hare and Midway airports and one small tract that has no housing reported on the American Community Survey.

Patterns of Ticketing Across the City

The similarity in ticketing patterns across the city between speeding and red-light cameras begs the question of whether exposure to the two sets of cameras bear similarities.

In *Figure 3*, we show that the number of cameras within a 3-mile radius of each census tract for the two types of cameras are similar to one another. A census tract that has a high number of speed cameras within a 3-mile radius also has a high number of red-light cameras in close proximity. While exposure to these camera systems rises together, it is also true that the exposure to cameras does not show the same racialized pattern at the residence end as ticketing rates. However, it is important to note that ticketing can occur in any part of the city regardless of where a vehicle may be registered. What *Figure 3* also shows is that depending on where people's activities take them, their exposure to the two camera systems rises or falls together. Further, to the extent there are similarities in the geography of movement for residents in close-by tracts, encounters with these automated systems may bear similarity across space.

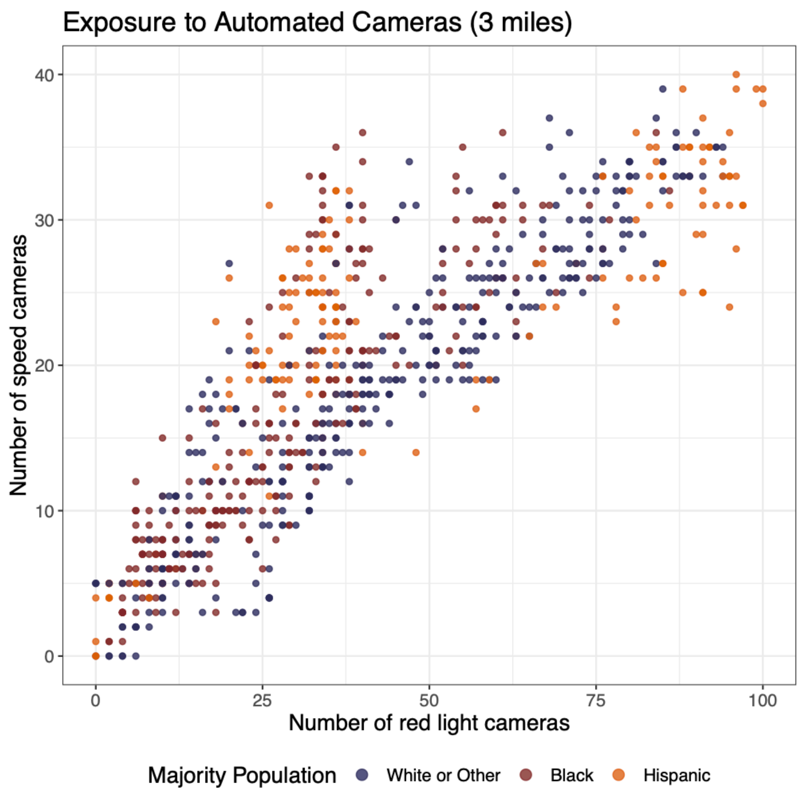


Figure 3 *Number of speed and red-light cameras within a 3-mile radius*

Key variables that we do not observe, but are critical to explaining the incidence of ticketing, are where and how much travel occurs by each vehicle. A vehicle that is able to avoid all the cameras in the city would have no tickets at all from the automated system regardless of how safe (or unsafe) the driver maybe. On the other hand, we can assume that a vehicle that is driven many miles a day would have some chance of exposure to the camera systems on some occasions. Unfortunately, neither of these measures of exposure – the geography of movement or the number of miles driven– are known to us. Instead, we use several variables at the census tract level, including household structure, number of proximate groceries, jobs per household and rideshare trips as driver, along with the number and type of cameras within certain catchment areas to approximate the amount of driving and thus exposure to cameras which may help explain the ticketing levels observed.

We also estimate the rates of ticketing at the camera level while controlling for traffic volume, type of camera, camera placement and socio-demographic variables in proximity to the cameras. Findings from the camera-level and census tract level analysis at are presented below.

Ticketing at the Camera Level

The number of tickets issued at a camera is going to depend on the number of vehicles that pass by it. In addition, the location of the cameras and the characteristics of the area in which they are placed may impact both driver behavior and the number of tickets issued. The ticketing levels for red light and speed cameras is done separately and reported below. This analysis uses all red-light and speeding tickets issued by cameras between 2016-2019 regardless of the residence area of the recipient.

Red Light Cameras

At red light cameras, ticketing levels range from 0.3 to 79.8 tickets per 10,000 vehicles per day. The average number of red-light tickets issued is 5.4 tickets per camera for every 10,000 vehicles in day. While ticketing levels depend on the amount of traffic on a roadway, attributes such as camera placement, roadway characteristics near the camera, and socio demographic characteristics may affect the number of tickets issued at a location. Using a regression model, we examine the tickets per 10,000 vehicles for each camera as a function of whether the camera is within 350 ft of a freeway, how far it is from a freeway, the road density within a square mile of the camera, violent crime levels in the vicinity of the camera (within a half mile buffer), and the majority race/ethnicity in the area.

The findings depicted in *Figure 4* show that cameras in close proximity to freeways (within 350 feet) issue higher level of tickets relative to cameras outside of that buffer. As the distance of red-light cameras to the nearest freeway increases, the number of tickets it issues, after accounting for traffic volume, declines. When road density in proximity to a red-light camera is high, the number of tickets issued decrease. When violent crime in proximity to a camera (within a half mile) increases, ticketing levels rise with it. Finally, red light cameras in majority Latinx/Hispanic areas tend to issue fewer tickets as compared to cameras elsewhere.

Figure 4 also shows the relative importance of the variables we control for. For continuous variables, the percentage change shows the expected increase/decline in tickets per camera for a two-standard deviation move in the variable. For binary variables, it indicates the difference between the attribute being true or false – for example, a camera being within 350 ft of freeways or not. The scaling offers a quick view that allows for comparison of importance among the variables.

Cameras in close proximity to freeways have a large impact on ticketing. A camera in such a location is expected to issue 170% more tickets all other things equal. From 2016-2019, cameras within 350 ft of a freeway only accounted for 12.8% of the red-light cameras but issued 32% of all red-light tickets. Looking across the city, red-light cameras within 350 feet of freeways constitute 21.2% of cameras in majority Black areas, 7.6% of cameras in majority Hispanic/Latinx cameras, and 10.4% of cameras in majority White or other census tracts.

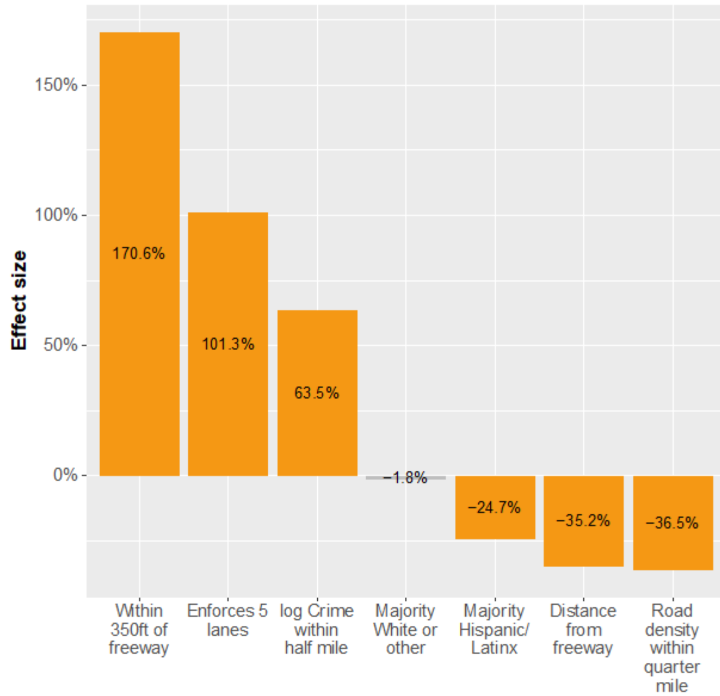


Figure 4 *Effect size of different variables on camera level ticketing rates based on standardized variables. Note the percentage changes indicate what would be expected for a 2 standard deviation move for continuous variables, all other variables held constant. For Binary variables, it shows the effect of the change from 0 to 1 – for example, from a camera not being within 350 ft of freeways to being within 350 ft of a freeway.*

The variables in *Figure 4* are in order of importance. Cameras that enforce 5 lanes issue more tickets than others. Currently, most red-light cameras enforce between 2-4 lanes and only four cameras enforce five lanes. Three of these cameras are in majority Black areas while one is in a majority Latinx/Hispanic area. These cameras on average issue double the tickets than other cameras. Increases in incidences of violent crime within half a mile of cameras is associated with higher levels of tickets, suggesting that drivers may behave differently in areas they deem unsafe.

Cameras that are in majority Hispanic/Latinx areas issue fewer red-light tickets than other areas. However, we find no difference in the ticketing rates between cameras in majority Black and majority White/Other census tracts after controlling for the other factors shown in *Figure 4*.

Cameras that are farther away from the freeway system tend to issue fewer tickets. Here again, we observe differences in the spatial distribution of cameras. The median distance-to-freeway for cameras in majority Black areas is 0.6 miles. That is, half the cameras in majority Black areas are within 0.6 miles of freeways. In majority Hispanic/Latinx areas, half are within 1.7 miles of freeways, and the median camera distance from freeways in majority White or other areas is 0.85 miles. Finally, cameras in places that have higher road density (measured as miles of roadway within a quarter mile buffer around the camera) tend to issue fewer tickets than cameras in places where the road density is less.

Figure 5 shows the daily rates of ticketing between cameras proximate to freeways and cameras that are more than 350 feet of freeways. These figures align with findings from the models.

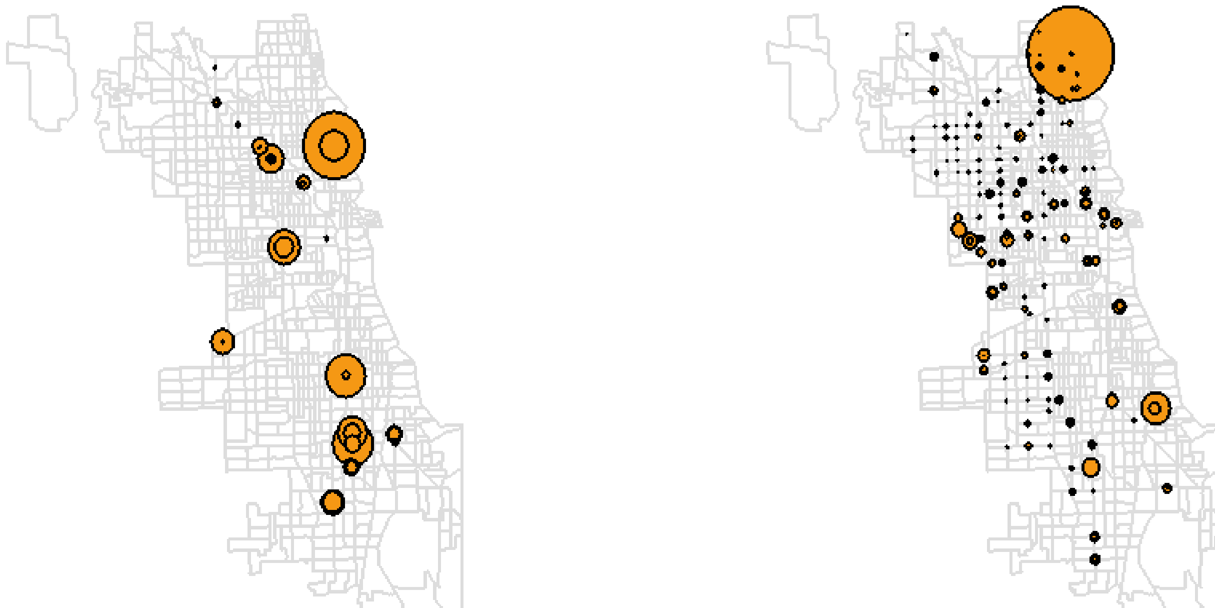


Figure 5 *Cameras within 350 ft of freeways (left) and Cameras outside of 350 feet of freeways (right). Bubble sizes reflect daily ticketing rates across cameras.*

Speed Cameras

Here we consider 149 cameras that were continuously operational between 2016-2019. All speed cameras are located in school and park safety zones. At speed cameras, ticketing levels ranged from 0.3 to 109 tickets per 10,000 vehicles per day. The average number of speeding tickets issued is 11.6 tickets per camera for every 10,000 vehicles in day. However, half of these cameras issued below 6.7 tickets per 10,000 vehicles per day

There are large differences in rates of ticketing among speed cameras that align with operating in a school safety zone or a park safety zone. School safety zone cameras are operational for fewer days of the year and have limited hours of operation.[11] While school cameras account for 46% of the 149 speed cameras considered here, they issued only 17.7% of the tickets between 2016-2019.

Using a regression model, we examine the tickets per 10,000 vehicles for each speed camera as a function of whether it is a school or park safety zone camera, road density within a quarter mile of the camera, population density in the tract that the camera is located in and the majority race/ethnicity in the tract the camera is located in.

Figure 6 shows the results of the model with the variables sorted by their standardized impact. As with red-light cameras, speed cameras in areas with higher road density issue fewer tickets, all other things equal, suggesting that road density (measured as miles of roadway within a quarter mile buffer of the camera) may have a calming effect on speeds. Cameras in areas of higher population density also tend to issue fewer tickets, suggesting that density also helps lower speeds.

Similar to red-light cameras, speed cameras in majority Latinx/Hispanic areas issue fewer tickets than in majority Black areas. The difference detected between majority Black and majority White/Other areas is not statistically significant.

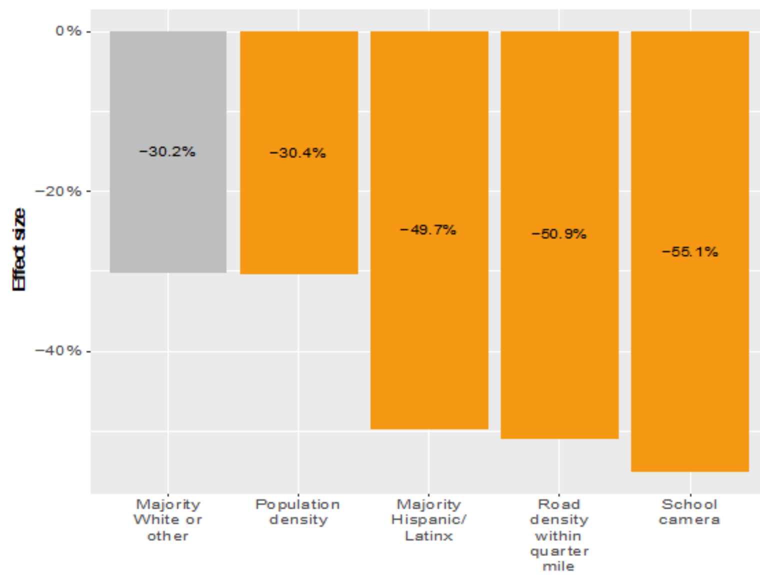


Figure 6 *Effect size of different variables on speed camera ticketing rates based on standardized variables. Note the percentage changes indicate what would be expected for a 2 standard deviation move for continuous variables, all other variables held constant.*

The distribution of school safety zone vs park safety zone cameras across Chicago differs by area demographics. School cameras, which only issue about 18% of speeding tickets, make up 71% of cameras in majority Hispanic/Latinx areas. In contrast, school cameras make up 33% of majority Black area speed cameras and 36% of majority White/Other area cameras.

In general, school safety zone cameras operate for fewer hours than park safety zone cameras and some school safety zones may enforce different speed limits when children are present. School cameras operate from 7 a.m. to 7p.m. on school days, while park cameras operate every day from 6 a.m. to 11 p.m. The higher concentration of school safety zone cameras in majority Hispanic/Latinx areas, their lower hours of operation, and differences in enforcement speeds, may account for some of the racial/ethnic differences captured by the model depicted in *Figure 6*.

Figure 7 shows the spatial distribution of speed cameras along with their intensity of ticketing. While the bubbles below can be compared between park (left) and school (right) zone speed cameras, they should not be used to compare to *Figure 5* which uses a different scale.

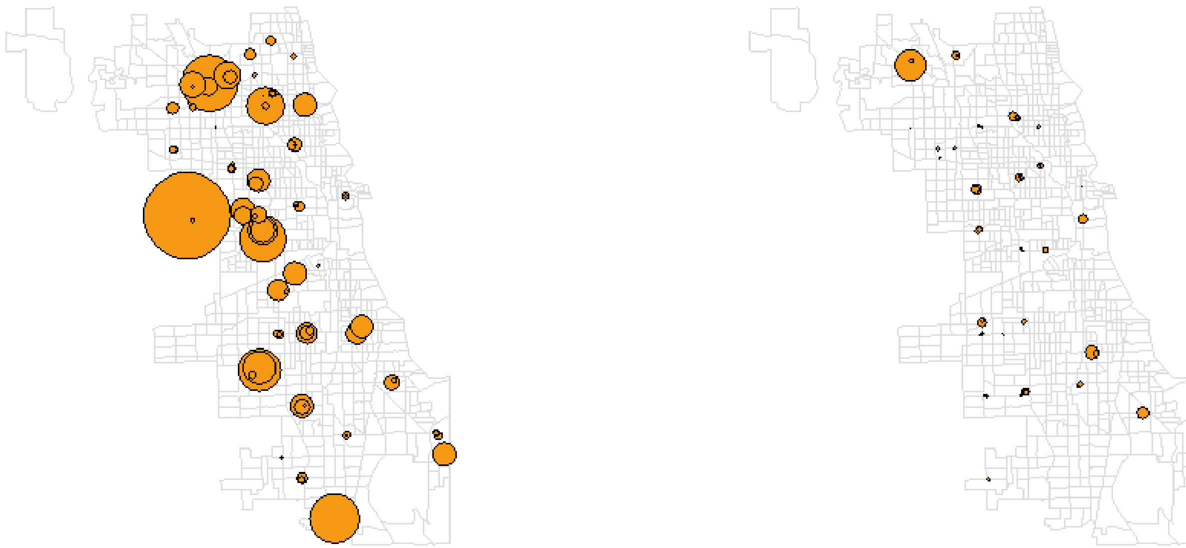


Figure 7 *Park safety zone cameras (left) and School safety zone cameras (right). Bubble sizes show the difference in daily ticketing rates across cameras. Part of the difference in ticketing rates is due to the limited hours and days that school safety zone cameras are operational.*

Ticketing at the Census Tract Level

Drivers may be ticketed by any of the cameras in the city based on their driving geography. In this section, we examine ticketing rates at the census tract level on a per household level. We explore what factors explain or correlate with ticketing rates at the tract level. The data used in this analysis are all tickets issued to Chicago households between 2016-2019 that we were able to geocode to a census tract.

As *Figures 1 and 2* above show, *tickets per household* for both speed and red-light cameras are higher in majority Black areas, followed by majority Hispanic/Latinx areas, and finally majority White/Other areas. At the *camera level*, however, we do not find such relationships. Cameras in majority Hispanic/Latinx areas tend to issue fewer tickets than others for both red-light and speed cameras. There is not a statistical difference in ticketing rates between cameras installed majority Black and majority White/Other areas for red-light cameras, and there is weak evidence that rates of ticketing by cameras in majority White/Other areas are lower than those in majority Black areas for speed cameras.

As we discussed earlier, ticketing rates will depend on exposure to the automated enforcement system, the characteristics of the roadway, as well as the built and social environment around cameras. In the absence of direct measure of exposure to cameras for households or census tracts, such as vehicles miles travelled, we employ other census tract level proxies that are likely indicative of travel behavior. These include jobs per household, children per household, percent multi-person households, household income, and number of rideshare trips made as driver by residents in a census tract. These variables are intended to capture how much people are likely to travel. For example, more jobs per household is likely associated with higher vehicle miles traveled (VMT) at the household level, and thus increasing exposure to the camera system. More children and multi-person households likely mean higher demand for travel. There may also be differences in VMT by income. Rideshare drivers likely travel many more miles each day as part of their job.

Second, we control for the number and type of cameras that residents in different tracts are exposed to proximate to their home tract as well as other built environment factors. We include the number of cameras within a 3-mile buffer of each census tract centroid, distinguishing between school and park cameras for speed cameras. We also control for the road density within a 3-mile radius of a tract, and the number of chain groceries within a 3-mile radius of a tract. The road density variable only captures road miles within Chicago. A lack of chain groceries near home likely means longer travel to access groceries and essential amenities.

Separate spatial error models are estimated for red-light and speed tickets per household at the census tract level. The data summary and the full models are reported in *Appendix A, Tables 3-5*. Below we show standardized estimates from the two models for a one-unit change in each independent variable. Continuous variables are standardized by two standard deviations; a one-unit move is thus equal to a change of two standard deviations on the original scale. The dependent variables are not standardized. For each model, the dependent variable is the number of tickets per household per year at the census tract level. *Figure 8* shows the standardized estimates from the model for red light tickets and *Figure 9* shows the standardized estimates for speed ticket model.

For red light cameras, majority Black areas have higher levels of ticket per household all else equal. Differences between majority Hispanic/Latinx and majority White/Other areas were not detected. Among the variables added as proxies for travel demand, jobs per household, average number of children per household, the percent of multi-person households are all associated with higher number of tickets per household. The number of rideshare trips made as a driver was not statistically significant in the red-light ticket model. Tracts with higher median incomes received fewer tickets per household, all other things equal.

Among variables used to capture exposure to cameras and built environment factors, the number of red-light cameras within 3 miles of census tracts has a positive effect (i.e., more cameras, more tickets). Tickets increase with roadway miles within a 3-mile radius of the census centroid. Finally, tracts that have more chain groceries within a 3-mile radius had fewer red-light tickets per household.

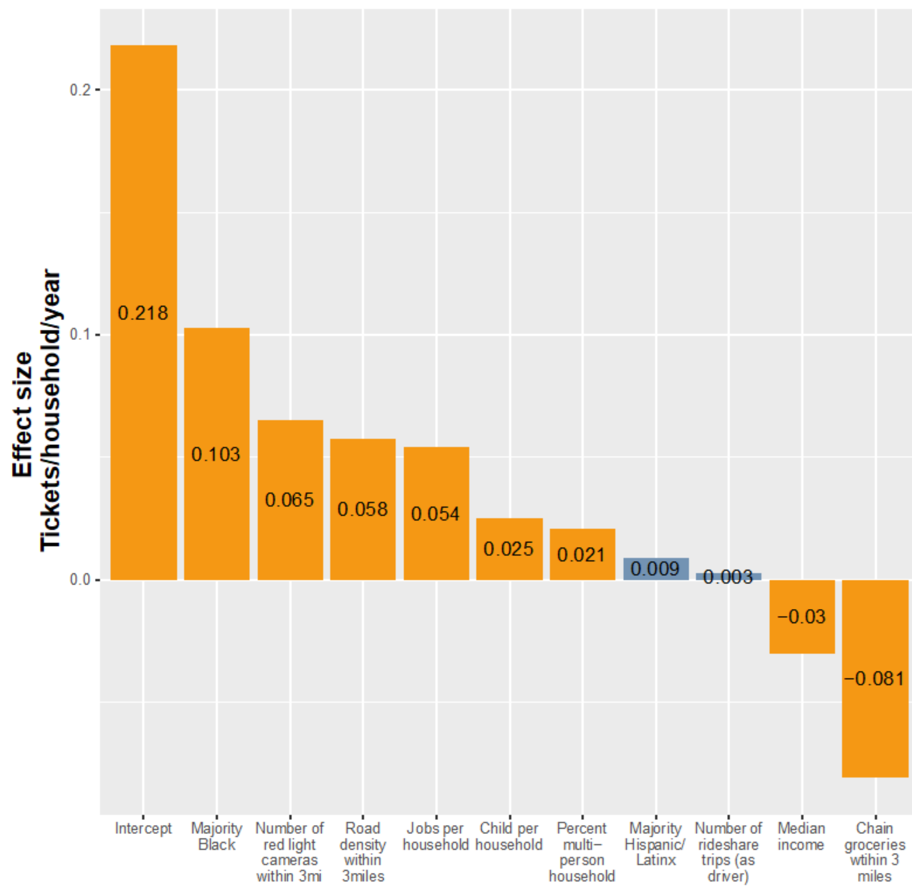


Figure 8 *Standardized model estimates for **red light tickets** per household per year (2016-2019) based on a spatial error model. Estimates in gray are not significant at p < 0.05.*

The results for the speed ticket model are mostly in line with red-light tickets, although there are some differences. Similar to red-light models, majority Black areas receive higher tickets per household than majority White/Other areas, but majority Hispanic areas also have a slightly higher ticketing rate than majority White/ Other areas. Similar to red-light camera tickets, jobs per household, children per household and percent multi-person households in a tract were associated with higher levels of ticketing. In the speed ticket model, median income was not important but the number of rideshare trips was associated with higher levels of ticketing on a tract per household basis.

Among the variables controlling for cameras and the built environment, the number of park speed cameras in a 3-mile radius of a tract was associated with higher levels of ticketing per household while the number of school cameras within the same radius was not associated with ticketing levels. Road density has a positive impact on ticketing similar to red light camera tickets. Finally, similar to ticketing levels for red light cameras, higher numbers of chain grocery stores were associated with lower levels of ticketing.

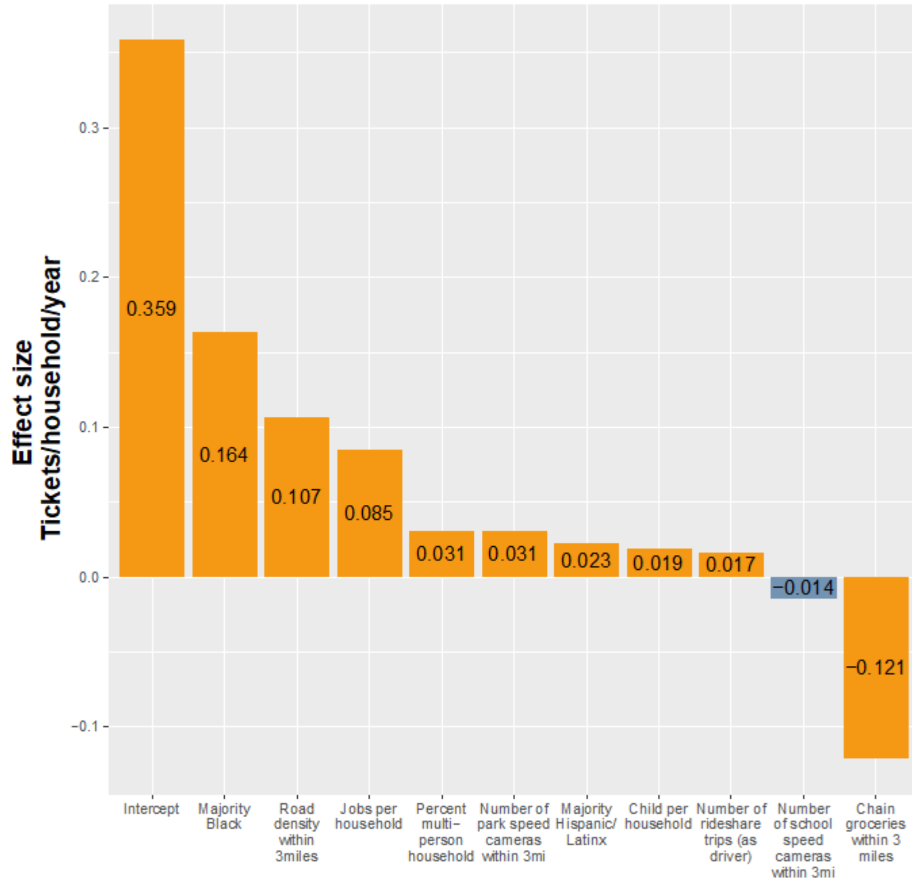


Figure 9 *Standardized model estimates for* ***speed tickets*** *per household per year (2016-2019) based on a spatial error model. Estimates in gray are not significant at p < 0.05.*

Both the red-light camera tickets and speed-camera tickets show that household structure variables expected to increase the amount of driving are associated with higher levels of ticketing. Exposure to the camera systems as well as built environment variables such as lower access to groceries are also associated with higher levels of ticketing. While differences based on the majority race/ethnicity variables persist in the model particularly for majority Black areas, our controls for travel levels are only approximate, and the race/ ethnicity variable maybe picking up differences in travel among tracts.

Conclusion

The analysis in this section looked at ticketing levels at both the camera level and at the census tract level. For red light cameras, we show that cameras within 350 feet of expressways issue significantly more tickets than other cameras after controlling for the volume on the roadway. Such cameras also constitute a higher proportion of the cameras in majority Black areas. Cameras enforcing 5 lanes, even though few in number, issue markedly more tickets than others. Three of these cameras are in majority Black areas while one is in a majority Hispanic/Latinx area. Additionally, higher levels of crime proximate to a camera was also associated with higher levels of ticketing. Cameras in majority Hispanic/Latinx areas issued fewer tickets, while differences in ticketing rates between cameras in majority Black and majority White/Other are not detected, all other things equal. The farther away a camera is for from expressways, the fewer tickets it issued. Cameras which have higher road density around them also issued fewer tickets.

For speed cameras, as expected, school safety zone cameras issued far fewer tickets than park safety zone cameras. Road density and population density around speed cameras are both associated with lower levels of ticketing after controlling for volume, suggesting a speed calming effect for both variables. Cameras in majority Hispanic areas issue fewer tickets after controlling for volume, but there was not a statistically significant difference between cameras in majority White/Other and majority Black tracts.

Even though we do not see a difference in ticketing rates per vehicle between cameras in majority White/Other areas and majority Black areas, and cameras in majority Latinx/Hispanic areas have lower ticketing rates, these results change when tickets are aggregated back to the census tract that the ticketed vehicles are registered to.

At the tract level, majority Black and majority Hispanic areas receive more red-light and speed camera tickets on a per household level. After controlling for a variety of camera exposure, built environment and household structure variables at the census tract level, the ticketing rates for majority Black areas are higher for both types of tickets. The differences in ticketing levels between majority Hispanic and majority White/Other areas, while smaller, persist for speed tickets, but disappear for red-light cameras. The differences between the camera level findings and the tract level findings suggest that there may be systematic differences in travel patterns (e.g., variables such as amount of travel, routes used, users per car, and cameras encountered on a per trip basis) for residents in majority Black areas that we are unable to control for.

From a policy perspective, the city should take a closer look at the red-light cameras proximate to expressways. As we discuss, these cameras issue a disproportionate share of tickets relative to their numbers in the system. The nature of the movement that is triggering a ticket to be issued at these (and other) cameras should also be examined. The city for example should discern between through and left turn vehicles that run a red light from those not making a full stop on a permitted right-turn on red. Adjusting fine levels on red-light cameras to the potential for harm is recommended either based on the movement type and/or the presence of pedestrians/bicyclists.

Ticketing at speed cameras is influenced by the built environment. Lower population densities and lower roadway densities pushup the ticketing rates at speed cameras after accounting for roadway volume. In areas where lower population density and roadway density are likely to increase speeds, the city should attempt to use other tools to lower speeds in lieu of or in addition to speed cameras. The city should also look at what drives placement of speed cameras given the higher proportion of school cameras in majority Hispanic/Latinx areas as compared to majority White/Other or majority Black areas.

05 ECONOMIC IMPACT OF PAID TICKET FINES AND FEES

Introduction

This chapter examines the distribution of camera-ticket fines and fees using an equity framework to explore the economic burden of camera ticket fines and fee for Chicago households.

As previously noted, between 2016 and 2019 Chicago's automated enforcement cameras issued 3,013,517 tickets, of which approximately 622,000 were speed warning tickets which carry no monetary fine. Warning tickets are excluded; the analysis in this chapter focuses on 2,391,464 monetized and geocoded speed and red-light tickets issued to Chicago households over four years. According to the Woodstock Institute's 2018 report, the City of Chicago issued citations for over 100 different vehicle-related offences, of which red-light and speed camera tickets constituted 30%.[12] Findings from this analysis show that between 2016 and 2019, approximately 72% of camera ticket fines ($100 or $35) and penalty charges ("fees") were paid, generating roughly $51 million annually from Chicago households.

This chapter uses the monetary sanctions literature as the basis for analyzing distributional effects of Chicago's camera tickets and attendant fines and fees. The literature engages multiple perspectives on the utility and effectiveness of monetized vehicle-related and non-vehicle related citations. Proponents of monetary sanctions argue that fines and fees are a deterrent for recurring infractions of administrative regulations, ordinances, and municipal codes.[13] Whereas opponents contend that fine levels and fees are driven by municipal budgets more than compliance.[14] Questions related to the disparate impact of fines and fees are also raised. There is general agreement that the typical payment structure of monetary penalties is a regressive tax that increases incrementally with nonpayment, thus disproportionately harming low-income residents.[15]

Moreover, monetary sanctions "disproportionately harm families of color, both due to discriminatory practices in issuing fines and fees and in the systemic issues of income and wealth inequities that make it more difficult for these families to pay."[16] Poor and working-class households are more likely to incur pecuniary penalties for nonpayment or late payment, which can lead to vehicle immobilization, towing, impounding and severe monetary penalties and collateral damages, which upper-income households are rarely subjected to.[17] Ability to pay precludes upper-income households from the most punitive effects of ticket fines and fees but may have negligible impact on driver compliance. As sociologist Carla Shedd notes, in unequal cities, the impacts of punitive policies are disparate and manifest both racially and spatially, and "ticketing can be a means of entry to the carceral continuum."[18] Similarly, fine and fee reform advocates assert that ticket-induced economic shocks disproportionately affect Black and Latinx communities, further sullying their relationship to law enforcement, widening the racial wealth gap, and, potentially, having adverse effects on city revenue if a substantial number of tickets go unpaid and municipalities incur the cost of debt collection.[19]

The lifesaving potential of traffic enforcement cameras is the most important criterion of camera efficacy. The empirical evidence on safety impacts is generally positive though periodically overshadowed by beliefs, both founded and unfounded, about automated traffic cameras as principally revenue generating technologies for city coffers and private vendors.[20] In jurisdictions with recent statutes eliminating the use of one or both types of automated traffic enforcement cameras, such as New Jersey and Texas, deactivation was contested. Public concerns about camera program transparency in implementation and ongoing operations, specifically methodologies for site selection and performance monitoring, criteria for camera removal, and potential racial and economic disparities resulting from onerous fines, fees, and forfeitures, fueled community contention.

Data and Approach

This section analyzes of red-light and speed camera ticket fines and fees data (2016-2019) and estimates the socio-economic and spatial distribution of economic burden.

The primary variables of interest include violation type (Red-Light, Speed 6-10 mph, Speed 11+ mph, Warning), original fine level ($100, $35, $0), payment status, total amount paid, and total amount due. These data were used to determine ticket fees, defined here as monetary assessments on any ticket, above the original fine, that accrues because of late or non-payment. We calculate ticket fees by differencing the original Fine Level and Total Payment, Fine Level and Amount Due, or a combination for partial payment. Ticket data was spatially joined to census tracts and merged with social, economic, housing and employment data from the U.S. Census American Community Survey 5-year estimates (2015-2019).

The distribution of red light and speed tickets by census tract is depicted in *Figure 1 (left)*. These are aggregate ticket counts, but distribution is comparable to the spatial pattern of ticketing per household presented in the previous chapter. *Figure 1 (right)* shows spatial clustering of the share of tickets paid by tract. On average, slightly more than 70% of tickets are paid, across tracts percent paid ranges from 32% to 98% over four years.

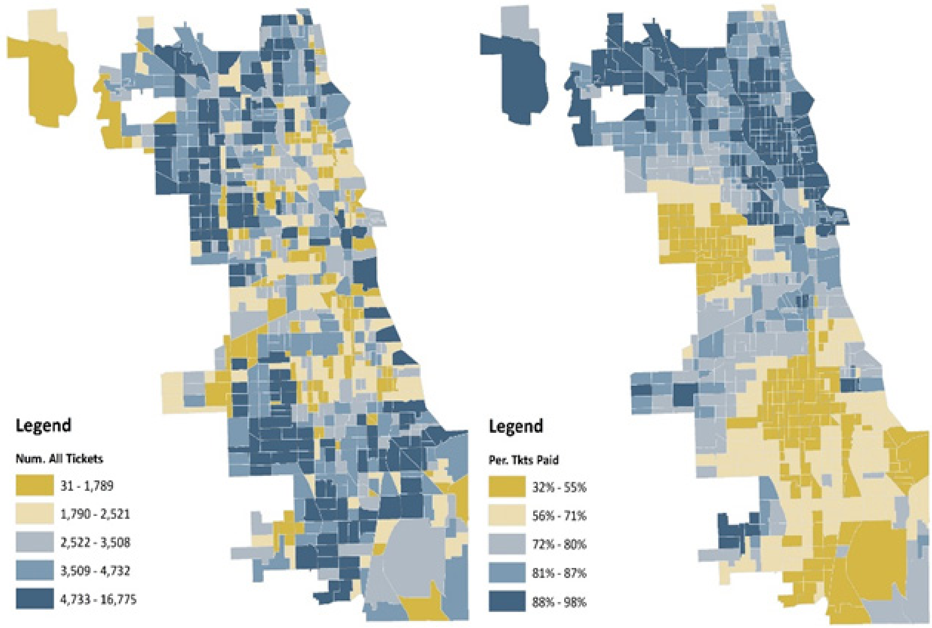


Figure 1 *Distribution of camera tickets by tract (left) and the share of paid tickets by tract (right)*

Measures of Economic Burden

This section summarizes the data and explains the three measures developed to estimate economic burden developed by tract. The next section focuses on the distribution of burden across the city by race and income.

Households paid $255,456 in ticket fines and fees, on average, with a standard deviation of $147,133 (*Table 1*). This corresponds to approximately $211 per household, with a range of $37 to $409. For nearly 20% of city tracts, households spent one standard deviation above the city average ($\mu + \sigma$): ($211 + $78) on camera tickets.

Table 1 *Data Summary for Paid Camera Tickets (2016-2019)*

Variables	Obs	Mean	Std. Dev.	Min	Max
Total Payment	798	$ 255,456	$ 147,133	$ 3,058	$ 1,357,559
Total Fines Paid	798	$ 194,798	$ 112,083	$ 2,170	$ 1,079,915
Total Fees Paid	798	$ 56,555	$ 38,490	$ 888	$ 266,761

Total payment as a share of aggregate household income is used to estimate the *Absolute Economic Burden* per census tract. *Absolute Burden* scores range from .024 to 1.49, with a mean =.368 and standard deviation = .239. This means that on average, .36% of household income went to pay camera ticket fines and fees between 2016-2019 [1sd ($\mu \pm \sigma$): (.368 - .239) to (.368 + .239) or 0.129 to .607]. Households in tracts with scores $\geq$.607 are most economically burdened by camera-ticket fines and fees paid. Conversely, households in tracts with scores $\leq$ .129 ostensibly experienced less burden. Average scores erase variability within tracts but offer a quick view of the distribution of economic burden across the city.

The second measure of economic burden is *Relative Income Burden*, measured as the share of total payment divided by the share of aggregate income per tract relative to the city overall. The *Relative Income Burden* depicted in *Figure 2* shows the spatial distribution of Income Burden. The average household in red tracts is considered burdened because they paid a larger share of fines and fees than their share of aggregate income in the city. In contrast, the average household in blue tracts is not economically burdened by camera ticket fines and fees relative to their income share.

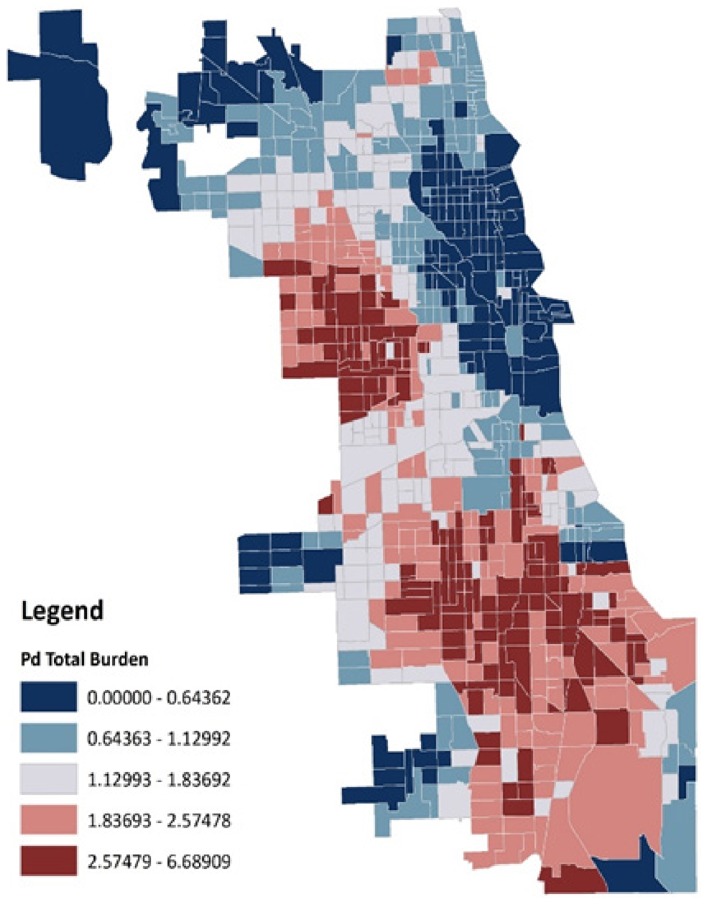


Figure 2 *Relative Ticket Burden*

We would expect the amount that any neighborhood pays toward tickets to approximate citywide income shares if the structure of ticket fines and fees were not regressive. Instead, the fines and fees regime in Chicago disproportionately burdens lower income households, which *Figure 2* shows manifests spatially and by majority race.

As a rule of thumb, tracts with scores >1.0 are considered economically burdened whereas tracts with scores <1.0 are not economically burdened by camera ticket fines and fees relative to their income share. Since the average total payment burden is above 1.0, we use 1sd ($\mu + \sigma$) as a better estimate of economic burden. Nearly 140 tracts (17.5%) have *Relative Burden* scores that are $\geq$2.71 or their share of paid fines and fees was 2.71 times their share of total income in the city.

Table 2 *Data Summary for Relative Income Burden*

Variables	Obs	Mean	Std. Dev.	Min	Max
Total Payment Economic Burden ($)	798	1.646	1.071	0.108	6.689
Economic Burden of Paid Fines ($)	798	1.563	0.900	0.119	5.479
Economic Burden of Paid Fees ($)	798	1.887	1.630	0.065	10.493

The third measure of economic burden is *Relative Ticket Burden*. This reflects ticket payment ($) as a share of the number tickets received (#) per tract relative to the city overall. From *Table 3* we see that *Relative Ticket Burden* for the average Chicago tract is closer to 1.0. This suggests that Total Payment as a share of tickets received per tract is on par with the city overall. The Burden of Paid Fees variable shows greater dispersion than Paid Fines, potentially suggesting distinct effects. In the next section *Relative Ticket Burden* associated with either fines or fees are analyzed separately.

Table 3 *Data Summary for Relative Ticket Burden*

Variables	Obs	Mean	Std. Dev.	Min	Max
Total Payment Burden (#paid tickets)	798	1.008	0.105	0.815	1.322
Burden of Paid Fines (#paid tickets)	798	1.001	0.013	0.960	1.038
Burden of Paid Fees (#paid tickets)	798	1.027	0.409	0.321	2.236

Racial and Economic Effects of Fines and Fees

Ticket fines and fees do not affect households equally. The regressivity of Chicago's ticket fines and fees means economic burden is disproportionately borne by lower income residents who are disproportionately Black and Latinx.

The scatter plot below in *Figure 3* illustrates *Absolute Economic Burden* of camera ticket fines and fees for tracts by income and majority race. Had the plot produced a horizontal line, with a non-racial pattern, we would say that the effects of fines and fees are similar across neighborhoods. Instead, *Figure 3* shows stark racial and economic inequalities. Median income for most majority Black and majority Latinx tracts is less than $50,000. In some instances, majority Black tracts pay as much as 1.5% of household income toward camera ticket fines and fees over four years. Majority Latinx neighborhoods paid upwards of .75% of household income on camera tickets over four years, but most paid less than .5%.

In *Figure 4*, *Relative Economic Burden* for fines and fees are plotted separately. They have a similar concave pattern but use different scales, reflecting the wider variability in the share of Paid Fees as a share of income. This is particularly stark for low-income majority Black neighborhoods whose share of paid fees was upwards of 10 times their share of income in the city over four years. While these neighborhoods are outliers, majority Black neighborhoods pay a larger share of fines and fees relative to income than majority Latinx or majority White/Other neighborhoods.

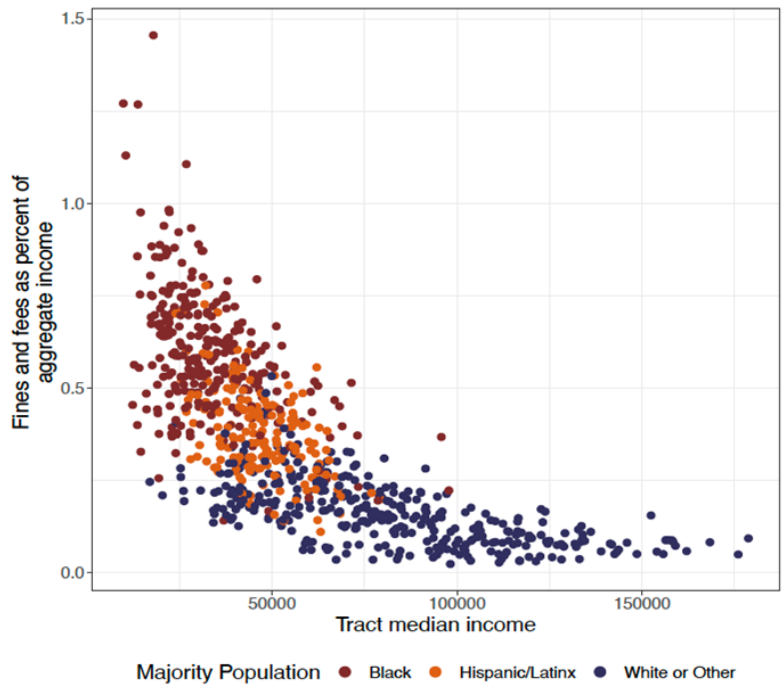


Figure 3 *Paid fines and fees as share of income or "Absolute Economic Burden"*

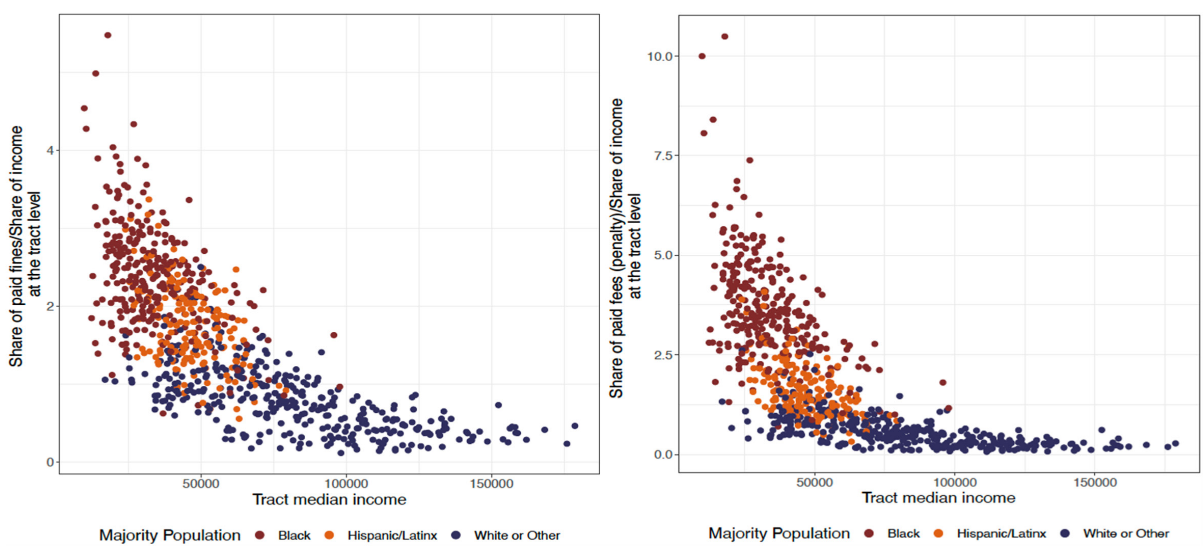


Figure 4 *Share of paid fines (left) and share paid fees (right) relative to income*

The share of Paid Fines and the share of Paid Fees relative to share of tickets received is presented in the box and whisker plot shown in *Figure 5*. The boxplots illustrate that the share of Paid Fines (*left*) is comparable to the share of tickets received across income groups. This should not be interpreted as Paid Fines are not associated with economic burden. There may be adverse economic effects but, on average, Fines Paid are what is expected relative to the number of tickets received.

The findings depicted in *Figure 5* for the share of Paid Fees (*right*) tell a different story. Low-income households paid a higher share of ticket fees relative to the number of tickets received. Over four years, the share of Paid Fees was, on average, 1.5 times the share of tickets received by drivers in low-income neighborhoods and could rise as high as 2.25 times. Recall that measures of *Economic Burden* only include paid tickets. Had the measure included both paid and unpaid tickets, the disparity for fees accrued relative to tickets to be even greater between lower- and upper-income neighborhoods as unpaid tickets are more concentrated in lower-income neighborhoods compared to upper-income neighborhoods, 40.7% and 7.14% respectively.

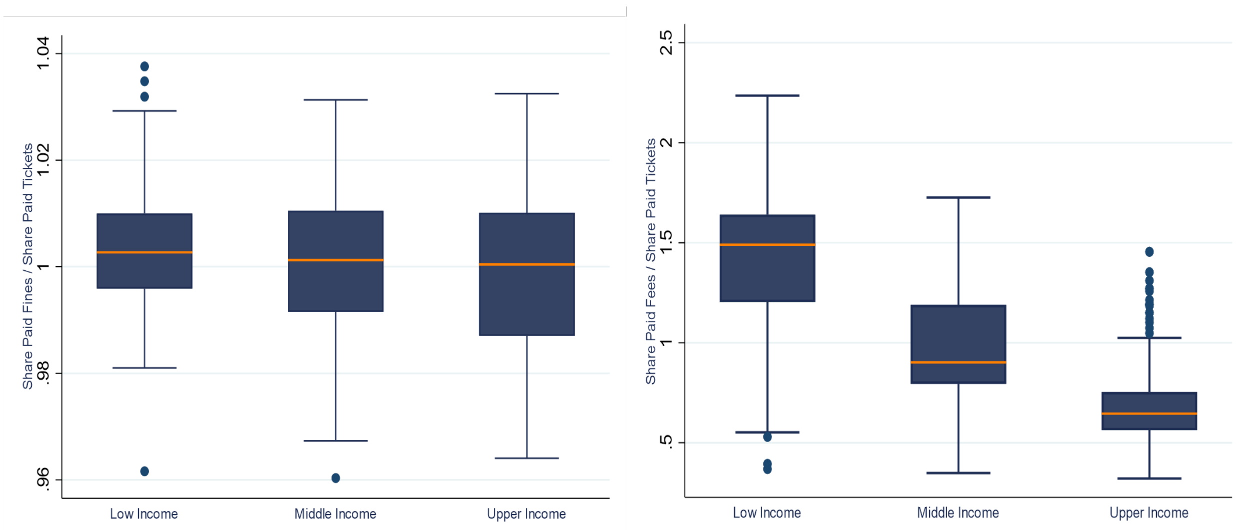


Figure 5 *Share paid Fines (left) and share paid Fees (right) relative to tickets*

Probability of Paying Tickets

The previous section shows disparate impacts of camera ticket fines and fees for the approximately 70% of tickets that were paid between 2016 and 2019. This section uses regression models to examine the likelihood that tickets are paid in varying conditions including vehicles accumulate multiple tickets and tickets accrue fees. The purpose of these models is to analyze individual-level heterogeneity for tickets that were paid. Unfortunately, theoretically relevant social and economic attributes are not available at the individual level. Instead, individual-level tickets are linked to recipients' census tract for socioeconomic measures likely to influence payment such as income status, percent in neighborhood not working, and majority race of neighborhood.

Linear probability models are used to examine three possible outcomes: 1) the probability that tickets are paid if drivers receive more than one ticket in four years; 2) the probability that tickets accrue fees; and 3) the probability of payment if tickets accrue fees. The results of the regression models are presented in *Appendix B, Table 1*. The probability any ticket is paid is also modeled. The results are not presented because they are not discernably different from the probability of paying conditioned on vehicles having more than one ticket (*Model 1*).

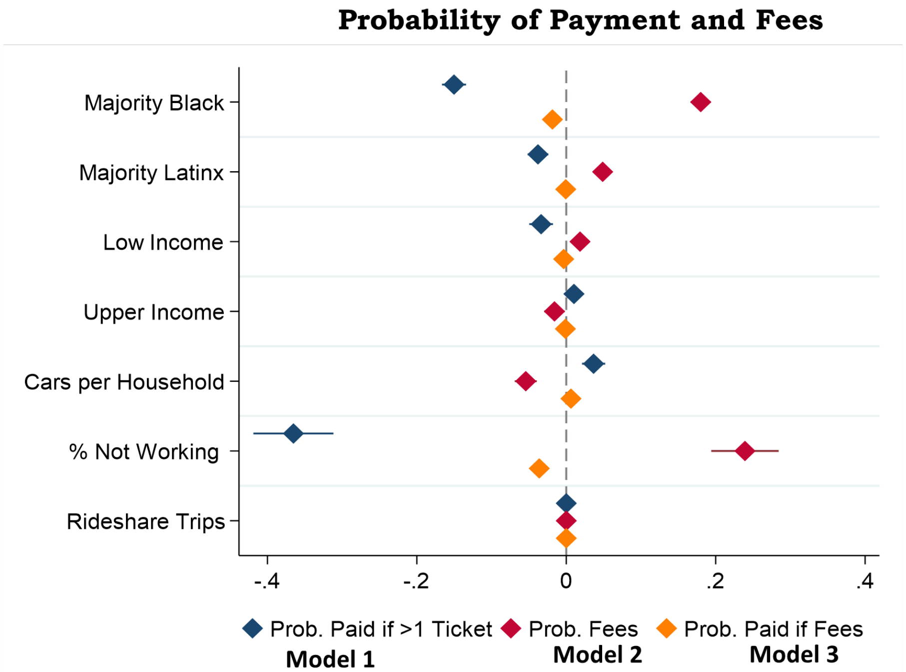


Figure 6 *Standardized coefficients for linear probability models. Model 1 is the probability tickets are paid if vehicle has >1 ticket, Model 2 is the probability tickets accrue fees, and Model 3 is the probability tickets with fees are paid*

Figure 6 shows the standardized coefficients from the three regression models. The benefit of presenting standardized coefficients is to give a common point of reference for comparing the relative importance of variables in the model that may be measured in different units or scales. *Model 1* illustrates the probability tickets are paid if a vehicle has more than one ticket. The model shows that with every increase of one standard deviation in the percent of residents not working, the probability of payment vehicle has more than one ticket decrease by .365 standard deviations, assuming other variables are held constant. Among the socioeconomic and other control variables, the percent of neighborhood residents not working, potentially a measure of ability to pay, is most strongly associated with the probability of payment. Majority Black neighborhoods, Majority Latinx neighborhoods, and low-income neighborhoods are negatively associated with the probability of payment if vehicles have more than one ticket.

Model 2 shows the standardized findings of the regression models for the likelihood that any ticket accrues fees. It makes sense that the direction of the variable coefficients in this model are opposite *Model 1*, but the relative importance of variables remains the same with the percent of residents not working and Majority Black areas having the largest impact on whether tickets accumulate fees. The other factors in the model are significant but of less importance, controlling for the other factors shown. *Model 2* includes both paid and unpaid tickets. For the probability that tickets with fees are paid (*Model 3*), we find no difference between upper income and middle-income census tracts after controlling for the other factors. All three models show little of no difference for upper income tracts relative to middle income. The probability of payment is not sensitive to income for households in the middle and upper strata.

Conclusion

The analysis in this chapter examined the distribution of Chicago's camera ticket fines and fees to assess economic impacts across neighborhoods and households and the probability of payment. The regressivity of ticket fines and fees is estimated with measures of economic burden. We find that economic burden (payment as a share of income) of ticket fines and fees is disproportionately borne by Chicago's Black, Latinx, and low-income residents. To better account for income and population variability across tracts, we examine the relative economic burden for tracts as a share of aggregate income, and as a share of aggregate tickets received.

We find that although Black, Latinx and low-income residents pay a disproportionate share of fines and fees relative to income, fees alone are particularly harmful for low-income residents. Residents of low-income tracts incurred fees on 46% of all tickets received compared to just 17% for those living in upper-income tracts. For tickets that were paid, fees were incurred on 34% of tickets going to low-income tracts and on 16% of tickets going to upper-income tracts. We also note that residents in low-income neighborhoods pay a higher share of ticket fees relative to aggregate income as well as relative to the number of tickets received. These findings suggests that racial and income disparities associated with camera ticket fines and fees cannot be fully explained by the number of tickets received.

Linear probability models were used to examine neighborhood factors that affect the likelihood of accumulating ticket fees and the likelihood tickets with fees are paid. Residents in majority Black, Latinx, and low–income neighborhoods have a much higher likelihood of accruing fees on any ticket and a much lower likelihood of paying a ticket once they have accumulated fees or more than one ticket. However, the standardized coefficients show that the percent of residents not working in a neighborhood is the most important factor associated with the probability of ticket payment and accruing fees.

Given these findings, we offer the following policy recommendations to the City of Chicago. Introduce a camera ticket fine structure that is commensurate with the risk of harm. As discussed, the risk of harm for all traffic infractions is not the same. For example, running a red-light through a major intersection has greater potential for severe injury than a rolling right turn violation. Yet they carry the same $100 fine. The city currently employs a graduated pricing structure for speed violations ($35 and $100). A similar pricing structure should be introduced for red-light violations. We also suggest reducing economic burden for low-income households by eliminating the doubling of fines as penalty for late payment, introducing caps on late fees, and implementing a statute of limitations for non-payment.

The city should implement a progressive fine and fee structure. There are multiple variants of progressive fine systems that improve compliance and do not negatively affect road safety.[21] We recommend developing fine and fee pricing system that considers the type of violation/severity of harm, number of vehicle infractions, and ability to pay. Eliminating the doubling of fines as penalty for late payment, introducing caps on late fees, and implementing a statute of limitations for non-payment would help to reduce economic burden for low-income households.

The idiom "don't do the crime, if you can't do the time" has been used in debates about the pricing of automated enforcement camera tickets as if to suggest the technological enforcement system creates a neutral playing field. drivers unable to afford to pay tickets should abide by the rules. There are no repercussions for drivers who can afford to pay tickets, even if they repeatedly flout traffic rules. Over four years, 23% of camera tickets were issued to drivers residing in low-income areas, and 19% of tickets went to drivers in upper-income areas. The current structure of fixed fines and rising fees pricing is fundamentally unjust because it disproportionately punishes Chicago's low-income households with marginal adverse effects for upper-income households despite accumulating more than 500,000 tickets in four years.

06 THE SAFETY IMPACTS OF CHICAGO'S SPEED CAMERAS

Introduction

This chapter examines the safety impacts of speed cameras in Chicago. In Illinois speed cameras are permitted within 1/8th of a mile of a school or park in municipalities with a population of over one million. These 1/8th mile buffers are termed Safety Zones. The state also allows the use of speed cameras in construction or maintenance zones when workers are present.[22] While Chicago has approximately 1500 safety zones, the city has set a 20% limit as to how many can have automated speed cameras. In addition to automated cameras, the city uses a variety of strategies including enhanced signage, better road markings, pedestrian refuge islands, etc. to enhance safety in Safety Zones.[23]

Chicago started installing automated speed cameras in 2013. As of 2019, there were 161 automated speed cameras operational in the city. In all, 142 of the 161 cameras were installed in 2013 and 2014. The hours of enforcement for these cameras depends on whether the camera is installed in a school or a park Safety Zone. School cameras operate from 7 a.m. to 7p.m. on school days, while park cameras operate every day from 6 a.m. to 11 p.m. The first speed violation triggers a warning ticket with no fines. Thereafter, the registered owner of the vehicle is fined $35 when cars are travelling 6-10 mph over the speed limit or $100 when speeds exceed 10 mph. In practice, the $35 tickets were only issued when speeds were at 10 mph over the limit until 2021. The city has changed this policy starting in 2021 so that all those traveling in the 6-10 mph over posted limit are issued tickets.

According to the city, the location of cameras is based on a "model that ranks safety zones based on total crashes, crashes involving a pedestrian or bicyclist, speed related crashes, serious/fatal crashes, crashes involving a person 18 or under." The location is further determined by speed studies and other equity considerations.[24]

The analysis in this section focuses on cameras that were installed in 2013 and 2014 and continued to be operational through 2015-2017. The paper examines all injury and fatality crashes that occurred within a 250m buffer of the cameras on the instrumented road. Because buffers overlapped for some cameras, the analysis looks at 101 camera locations.

Background

According to the National Highway Traffic Safety Administration (NHTSA), speeding was a factor in 26 to 31% of crash fatalities annually in the U.S. from 2009 to 2018. Because of the impact energy involved, injuries in high-speed crashes are more likely to be severe or fatal. As a result, policy makers often allocate significant effort to curb speeding. These range from the posting of prominent speed limit and other signage, variable messaging signs, placement of speed bumps and other calming structures, and various enforcement actions including spot enforcement by officers. Automated speed enforcement has also become one of the mechanisms employed to enforce speeding laws and reduce speeds since the 1980s.[25]

Much of the evidence on automated speed camera enforcement indicates that the cameras are effective at reducing injury crashes. One review looking at 14 studies finds collision reductions of 5-69%, injury reduction of 12-65%, and a reduction in death of 17-71%.[26] Another study which looked at 13 studies reported a 20-25% reduction as the best estimate of injury crash reductions at fixed camera locations.[27] A third study that summarize six studies that report reductions in personal injury accidents in the range of 9% to 51% and a reduction in the range of 6% to 40% in fatal or serious accidents.[28] An evaluation of the camera program in the U.K. also showed a decline in people exceeding the speed limit in camera locations.[29] The general findings suggest that cameras enhance safety, but there is a high degree of variation in their degree of effectiveness based on the locations being studied. Some of the variation may also have to do with the methodologies adopted.

Data and Approach

The analysis in this section relies on multiple data sources. Crash data for the period from 2010-2017 with geocoded data locations and injury types was received from the Illinois Department of Transportation. Each crash incident is coded with the injuries associated with it. In Illinois, injury classifications are coded as K when a fatality occurs, A when an incapacitating injury occurs, B when a non-incapacitating injury occurs, and C when an injury is reported or claimed that is not among the ones that fall in categories K, A, or B. Crashes coded as O, which stands for no indication of injury, are not included in this analysis. In any crash incident, multiple types of injuries may occur on persons involved. The most severe type of injury reported is used to classify each crash as type K, A, B or C in this analysis.

Other data used in this analysis includes the roadway volume, which is based on IDOT's Getting Around Illinois website, and Chicago's speed cameras for the post-installation period for the treated sites. The roadway geometry data is based on roadway data from Chicago's Open Data Portal, and population figures from the U.S. Census were also employed to compute population density.

The analysis focuses on 101 speed camera instrumented locations. Changes in the count of injury crash incidents within 250 meters on either side of the cameras along the instrumented road over a three-year period are used as a basis for evaluating safety. *Figure 1* shows the number of fatality and injury crashes observed at the 101 sites included in the study by year.

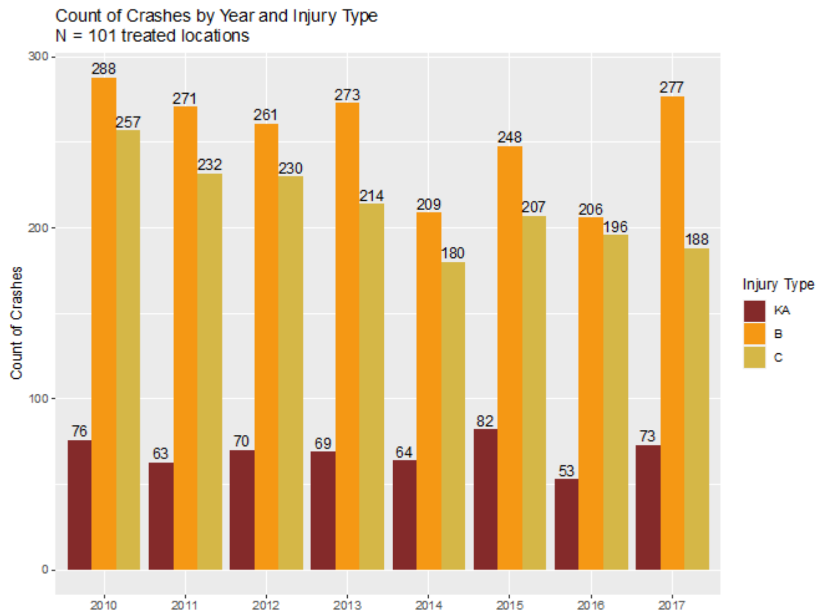


Figure 1 *Injury Crash Counts within 250 meters on either side of a camera location for 101 sites from 2010-2017.*

The Empirical Bayes (EB) method is used to examine the safety impacts of Chicago's speed cameras. The analysis uses an observational before-after approach and estimates safety by comparing the after-period crash counts against *what would have happened if cameras were not installed at the treated sites*.[30] Since most speed cameras in Chicago were installed in 2013 and 2014, the 2010-2012 period is taken as the "before treatment" period and the 2015-2017 period is used as the "post treatment" period in this analysis.

Direct comparison of before and after period crash counts are inappropriate for a number of reasons. First, treated sites often are chosen based on the count of crashes, which often naturally fluctuate. Excessively high crash counts, which may have led to camera installation, are often followed by lower counts without treatment due to the regression-to-the-mean phenomenon. Direct comparison therefore often overestimates the safety benefits of interventions. Second, in the after period, volume or other changes may have occurred on treated roadways that alter its safety profile. In addition, there may be long run changes in crash outcomes due to technology, weather or other factors that a direct before-after comparison may attribute to the intervention. The approach followed here attempts to tease out these factors by comparing the observed crash record against what would have been expected to happen if speed cameras were not installed at the treated locations.

The EB method is implemented as follows. First, locations that could have had a speed camera installed (but did not) are identified to assess the safety performance of roadways in safety zones in the before and after periods. These sites are used to estimate models, often called safety performance functions (SPFs), that estimate the number of expected crashes over some specified period given traffic and geometric conditions on roadways. The SPFs, along with the characteristics of the treated sites, are then used to estimate the expected number of crashes on the 101 treated locations on the basis of their measurable attributes. These estimates provide a base line for how unsafe a typical location with the characteristics of the treated sites is. This estimate is then combined with the prior crash record of the treated sites to estimate the expected crash count for each location.

SPFs for the after period, along with roadway characteristics in the after period on treated sites, are also used to estimate expected crash numbers on typical roadways post-treatment on facilities that match the characteristics of the treated sites. These estimates, along with the pre-treatment period crash estimates for each site, are used to predict what would have happened had cameras not been installed at the treated sites (the counter-factual case). A comparison of the counter-factual case against what actually happened gives an estimate of the impact that cameras had on the safety record at each location. The SPFs and the technical details are provided in *Appendix C*.

Safety Impacts

We examine safety impacts both at the aggregate level across all sites and at the site level in the following two sections.

Overall Safety Impacts

The results from the aggregate safety impacts assessment are given in *Table 1*. Over the 3-year period from 2015-2017, we estimate that there were 36 fewer KA type injury crashes, 68 fewer type B crashes, and 100 fewer type C crashes across the 101 locations. In all, there were 204 fewer injury crashes. Reductions of type A and C crashes were estimated at around 15% and that for type B injuries at 9%. Overall, speed cameras led to a 12% reduction in injury crashes.

The overall estimate of safety improvement is smaller than what a direct comparison of before and after crash counts would have estimated. A simple comparison of the 2010-2012 crashes against the 2015-2017 crashes yields an overall reduction of 218 crashes as opposed to 204 crashes. It would underestimate the total K and A crash reductions (estimated as a change of 1 as opposed to 36) and overestimate the reductions in B and C injury crashes (a reduction of 89 and 128 respectively as opposed to the 68 and 100 shown in *Table 1*). Such an estimate would not have accounted for the regression to the mean phenomenon that occurs when high-crash locations are selected for treatment or how crashes changed in the after period based on the SPFs from the reference safety zones (*i.e.*, the treatable but untreated sites used to estimate SPFs).

Table 1 *Estimated Safety Impacts of Speed Cameras by Crash Injury Type*

	KA injuries	B injuries	C injuries	Overall
Observed crashes 2015-2017	208	731	591	1530
Expected crashes without cameras 2015-2017	244	799	691	1734
Estimated reduction in crashes	36	68	100	204
Accident Modification	14.9%	8.6%	14.5%	11.8%

Site Level Impact Assessment

While on aggregate, the speed cameras improve safety, there is some variation in how successful they have been at the camera level. Of the 101 sites in this analysis, 93% had a safety improvement estimated in at least one injury type. In 71% of sites (N = 72), we could be 90% confident that the estimated improvement in at least one injury type was greater than zero. Only seven sites had an estimated crash increase across all injury classes.

Table 2 summarizes site level improvements by injury type. Safety improvements for KA, B, and C injury types were seen in 60-66% of sites based on injury type. We could be at least 75% confident that there was an improvement in the crash outcomes in 44-50% of instrumented locations by injury type. If we apply a more stringent 90% confidence threshold for improvements, between 34-40% of sites show a reduction in crashes for different injury types.

Aggregating across all injury crashes (KABC), we see safety improvements in 70% of cases. At 54% of the sites, we could be at least 75% confident we have a non-zero improvement in the overall reduction of crashes. At the higher threshold of 90% confidence, 37% of the treated sites saw an improvement in overall crashes. On the other hand, between 33-40% of sites had an estimated increase in crashes. In 14-20% of the cases by injury type, we could be about 90% confident that these increases in crashes were significantly different from zero. Two thresholds at 75% and 90% are used in part to emphasize that different decision makers may make differing assessments of what is a desired level of confidence in these improvements. The estimated changes in the number of crashes for the sites in this analysis is reported in *Appendix C Table 3*.

Table 2 *Site Level Safety Improvemennt Estimates by Camera Location*

	KA	B	C	Overall
N sites crashes declined	63	61	67	71
proportion	62%	60%	66%	70%
N sites crashes declined with $p > .75$	48	44	50	54
proportion	48%	44%	50%	53%
N sites crashes declined with $p > .90$	37	30	36	37
proportion	37%	30%	36%	37%
N sites crashes increased	38	40	34	30
proportion	38%	40%	34%	30%
N sites crashes increased with $p > .75$	29	27	24	19
proportion	29%	27%	24%	19%
N sites crashes increased with $p > .90$	20	17	14	13
proportion	20%	17%	14%	13%
Total sites	101	101	101	101

Based on the site level estimates, *Figures 2-4* show the actual and expected crashes at each location included in the analysis. In total, 43 sites had reductions that exceeded one standard deviation of the expected number of crashes. These are shown in *Figure 2* as showing marked improvement in their safety record. These sites primarily accounted for the benefits of the speed camera program, accounting for a total reduction of 294 fewer injury crashes. Another 42 sites had crashes within one standard deviation of what was expected without cameras. In total, the net reduction in KABC crashes from these sites was 36 fewer crashes. These are shown in *Figure 3*. Finally, 16 sites had an increase in crash frequency that exceeded one standard deviation of what would have been expected without cameras, accounting for an increase of 126 injury crashes in treated areas. *Figure 4* shows these 16 sites. The total reduction in KABC injury crashes of 204 across all cameras reported earlier is a total sum of the changes from these three sets of sites.

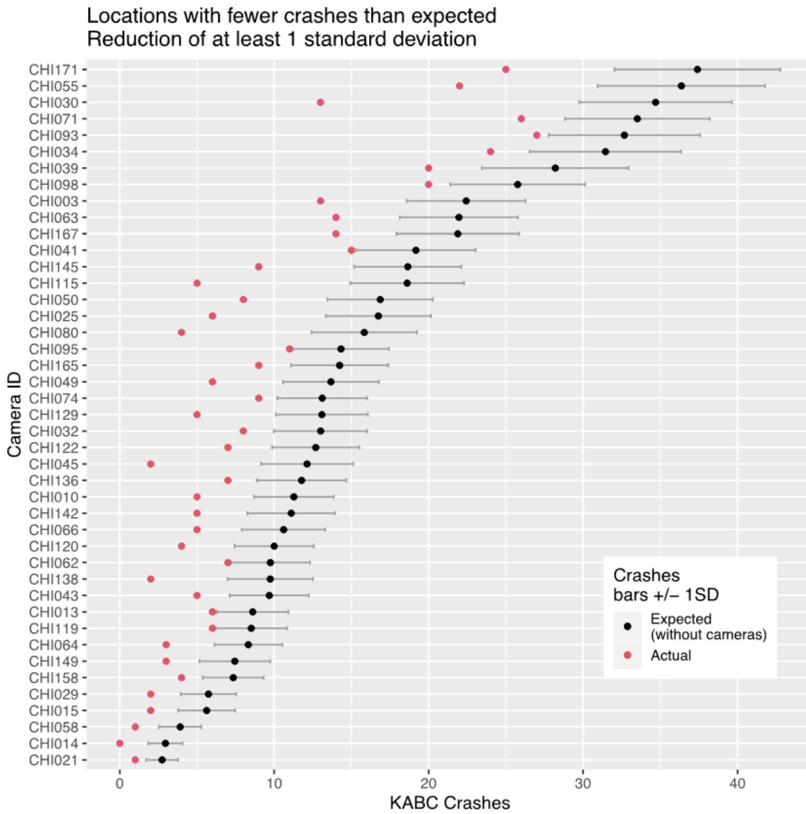


Figure 2 *Sites where the actual crash record was below what would have been expected by 1 standard deviation or more. Based on KABC crashes.*

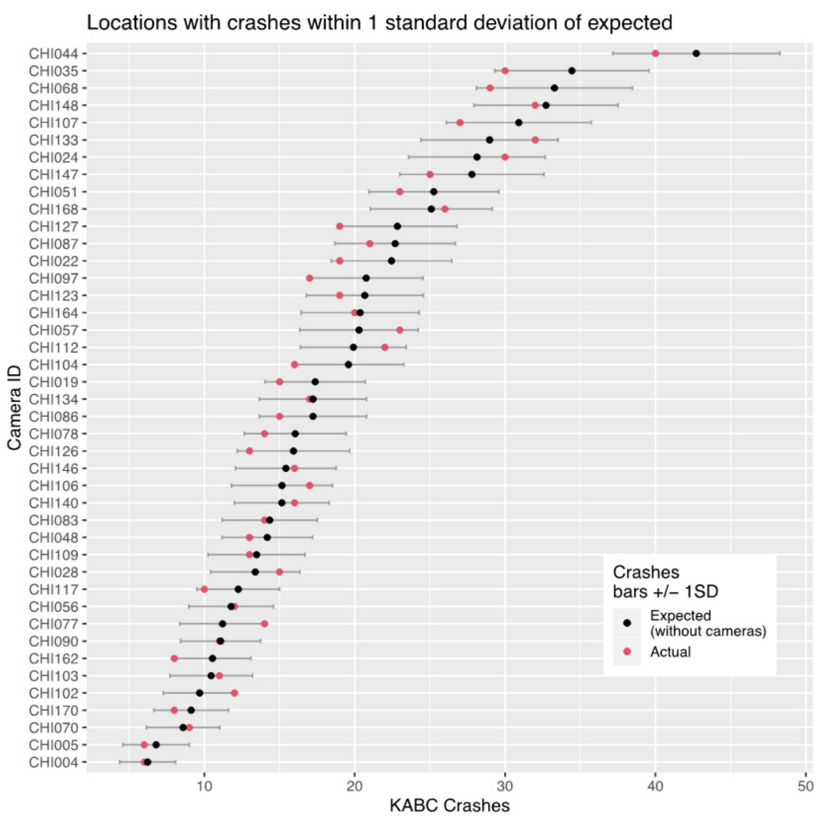


Figure 3 *Sites where the actual crash record in the after period is within 1 standard deviation of what would have been expected without cameras. Based on KABC crashes.*

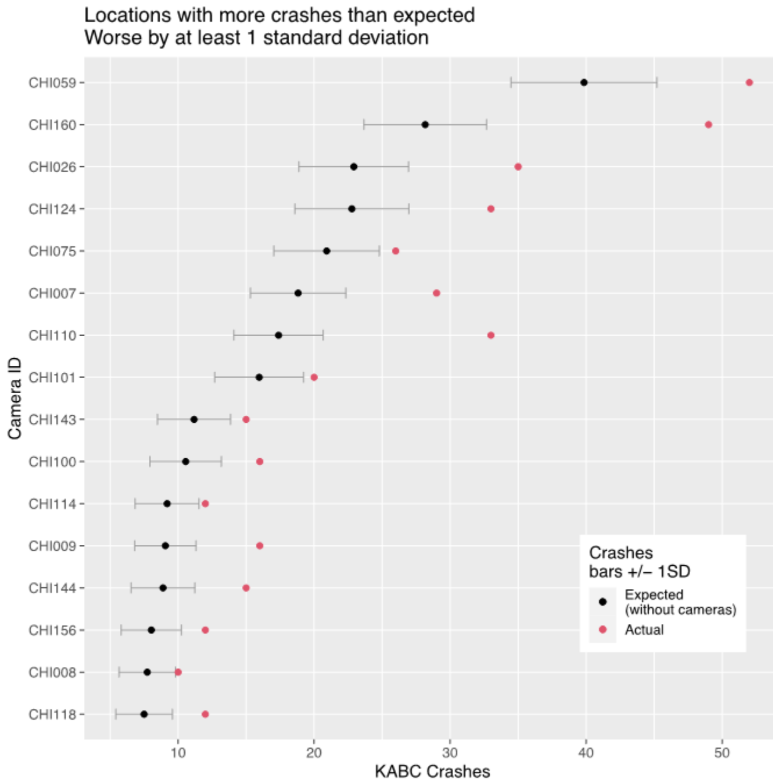


Figure 4 *Sites where the actual crash record in the after period has increased by 1 standard deviation or more of what would have been expected without cameras. Based on KABC crashes.*

Conclusion and Discussion

This chapter examined the effectiveness of automated cameras in Chicago while controlling for regression to the mean and time period effects. On aggregate we estimate a 12% reduction in fatal and injury crashes at treated locations within a 250-meter buffer from 2015-2017. The estimate for serious injuries and fatalities is about 15%. The overall performance of speed cameras in Chicago is within the reported range cited in the literature (see Background section), though on the lower side of estimates.

We also note that cameras were not universally effective across all treated sites. In 70% of locations, estimated crash reductions were greater than zero. In 43% of cases improvements in safety exceeded 1 standard deviation of expected without cameras. In 16% of cases, a marked increase, exceeding 1 standard deviation of expected, was also observed. In some locations, crash outcomes have not changed significantly or have worsened.

For the city of Chicago, some pragmatic recommendations can be made. As a first step, the city should closely examine the sites where crash outcomes have increased. It is possible that something fundamentally has changed at these sites in the after period that the models here were not able to capture. It may also be that crash outcomes have sources outside of speeding that require attention. Second, the city should examine the sites where conditions have not changed from the before period.

Related to both points above, the city should also look at the decision-making process it uses to decide where to deploy speed cameras. While the city states that crash frequencies inform decision making, the length of the crash history, the weights attached to crash events involving pedestrians, bicyclists or children in deciding placement is not clear. Reliance on relatively rare crash events or on short term spikes may lead to treatment of sites that are otherwise as safe as other untreated locations. Whether speed is the underlying cause for observed unsafety locations should also examined before deploying cameras.

Finally, the city should continuously review the effectiveness of cameras at different sites to ensure that each is delivering the safety benefits expected from it. Where cameras are found to be ineffective, turning them off, rotating them to other locations where speed is an issue, or using other interventions in lieu of cameras should also be considered.

Appendix A:
Technical Documentation of the Camera and Tract Level Analysis

Model of Red-Light Ticket Rates at the Camera Level

Table 1 *Model for ticketing levels at red-light cameras. Dependent variable is the natural log of daily tickets per 10,000 vehicles. Uses ticketing data from 2016-2019.*

	Estimate	Standardized estimates+	Standard Error	t value	Pr(>|t|)	
(Intercept)	0.990	1.370	0.322	3.074	0.002	**
Camera within 350 ft of a freeway (1 = Yes)	0.996	0.996	0.170	5.848	0.000	***
Distance from freeway (miles)	-0.225	-0.435	0.049	-4.632	0.000	***
Enforces 5 lanes	0.700	0.700	0.347	2.016	0.045	*
Road miles within quarter mile	-0.082	-0.455	0.019	-4.321	0.000	***
Log (Violent crimes within half mile)	0.272	0.492	0.059	4.612	0.000	***
Majority Hispanic/Latinx	-0.284	-0.284	0.112	-2.535	0.012	*
Majority White/Other	-0.018	-0.018	0.125	-0.142	0.887	
Residual std error:	0.6649 on 281 degrees of freedom					
Multiple R-squared:	0.3512					
Adjusted R-squared:	0.335					
F-statistic:	21.73 on 7 and 281 DF, p-value: < 2.2e-16					

Significance codes: <0.001 '***' <0.01 '**'. <0.05 '*' <0.1 '.'

+Continuous variables are standardized by subtracting the mean and dividing by 2 times the standard deviation. Binary variables remain on 0/1 scale. This allows for better comparison of importance of variables on ticketing levels across binary and continuous variables[31].

Model of Speed Camera Ticket Rates at the Camera Level

Table 2 *Model for ticketing levels at speed cameras. Dependent variable is the natural log of daily tickets per 10,000 vehicles. Uses ticketing data from 2016-2019.*

	Estimate	Standardized estimates+	Standard Error	t value	Pr(>|t|)	
(Intercept)	3.513	2.539	0.203	17.338	0.000	***
School camera (1 = Yes)	-0.801	-0.801	0.165	-4.853	0.000	***
Population density (population/acre)	-0.010	-0.363	0.004	-2.287	0.024	*
Road miles within quarter mile	-0.084	-0.712	0.019	-4.479	0.000	***
Majority Hispanic/Latinx	-0.688	-0.688	0.206	-3.343	0.001	**
Majority White/Other	-0.359	-0.359	0.191	-1.876	0.063	.

Residual std. error:	0.9028 on 143 degrees of freedom
Multiple R-squared:	0.4557
Adjusted R-squared:	0.4367
F-statistic:	23.95 on 5 and 143 DF, p-value: < 2.2e-16

Significance codes: <0.001 '***' <0.01 '**' <0.05 '*' <0.1 '.'

+Continuous variables are standardized by subtracting the mean and dividing by 2 times the standard deviation. Binary variables remain on 0/1 scale. This allows for better comparison of importance of variables on ticketing levels across binary and continuous variables.

Table 3 *Data Summary for Tract Level Analysis*

	Variable	Mean	Standard deviation
Ticketing data	Red light tickets per household per year	0.26	0.12
	Speed tickets per household per year	0.42	0.16
Camera and built environment variables	Number of red-light cameras in 3 miles	39.50	25.35
	Number of park speed cameras in 3 miles	10.11	5.23
	Number of school speed cameras in 3 miles	8.87	5.64
	Road density within 3 miles of tract	3.46	0.97
	Number of chain groceries within 3 miles	19.07	10.47
Census tract household variables and rideshare	Jobs per household	1.11	0.24
	Children per household	0.61	0.32
	Percent multi-person household	65.38	14.12
	Median household income (,000)	57.08	32.39
	Rideshare Trips (,000)	53.44	52.40
Majority race/ethnicity in a tract	Majority Black	35%	
	Majority White or Other	44%	
	Majority Hispanic/Latinx	21%	

Model of Red-Light Ticketing Levels per Household at the Census Tract Level

Table 4 *Spatial error model for red light tickets per household per year for Chicago census tracts. Continuous variables are standardized by subtracting their mean and dividing by twice their standard deviation. Dependent variable is not standardized.*

Variable	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	0.218	0.008	28.975	0.000
Majority Black	0.103	0.008	12.780	0.000
Majority Hispanic/Latinx	0.009	0.008	1.187	0.235
Number of park speed cameras in 3 miles	0.065	0.016	4.080	0.000
Road density within 3 miles of tract	0.058	0.014	4.086	0.000
Number of chain groceries within 3 miles	-0.081	0.014	-5.793	0.000
Jobs per household	0.054	0.005	11.025	0.000
Children per household	0.025	0.006	4.127	0.000
Percent multi-person household	0.021	0.006	3.325	0.001
Median household income (,000)	-0.030	0.007	-4.291	0.000
Rideshare Trips (,000)	0.003	0.005	0.510	0.610

Lambda: 0.770, LR test value: 259.96, p-value: < 2.22e-16

Asymptotic standard error: 0.027898

z-value: 27.606, p-value: < 2.22e-16

Wald statistic: 762.09, p-value: < 2.22e-16

Log likelihood: 1347.898 for error model

ML residual variance (sigma squared): 0.0017693, (sigma: 0.042063)

Number of observations: 801

Number of parameters estimated: 13

AIC: -2669.8, (AIC for lm: -2411.8)

Model of Speed Ticketing Levels per Household at the Census Tract Level

Table 5 *Spatial error model for speed tickets per household per year for Chicago census tracts. Continuous variables are standardized by subtracting their mean and dividing by twice their standard deviation. Dependent variable is not standardized.*

Variable	**Estimate**	**Std. Error**	**z value**	**Pr(>|z|)**
Intercept	0.359	0.009	38.339	0.000
Majority Black	0.164	0.011	14.384	0.000
Majority Hispanic/Latinx	0.023	0.011	2.073	0.038
Number of park speed cameras in 3 miles	0.031	0.016	1.961	0.049
Number of school cameras in 3 miles	-0.014	0.014	-1.008	0.314
Road density within 3 miles of tract	0.107	0.019	5.501	0.000
Number of chain groceries within 3 miles	-0.121	0.018	-6.810	0.000
Jobs per household	0.085	0.007	12.335	0.000
Children per household	0.019	0.009	2.147	0.032
Percent multi-person household	0.031	0.009	3.349	0.001
Rideshare Trips (,000)	0.017	0.007	2.250	0.024

Lambda: 0.705, LR test value: 193.64, p-value: < 2.22e-16

Asymptotic standard error: 0.032564

z-value: 21.654, p-value: < 2.22e-16

Wald statistic: 468.91, p-value: < 2.22e-16

Log likelihood: 1033.405 for error model

ML residual variance (sigma squared): 0.00399, (sigma: 0.063166)

Number of observations: 801

Number of parameters estimated: 13

AIC: -2040.8, (AIC for lm: -1849.2)

Appendix B:
Technical Documentation of the Fine and Fee Analysis

Probability Models of Fine and Fee Payment at the Ticket Level

Table 1 *Standardized coefficients from linier probability models estimating the likelihood of camera tickets and likelihood payment over four years.*

	Model 1 **Likelihood Ticket is Paid if Driver has > 1 Ticket**	Model 2 **Likelihood of Receiving Fees on Ticket**	Model 3 **Likelihood Ticket is Paid if Fees Accrue**
Majority Black	-0.150***	0.180***	-0.019***
	0.008	0.007	0.001
Majority Latinx/Hispanic	-0.038***	0.049***	-0.001
	0.007	0.006	0.001
Low Income	-0.034***	0.018**	-0.003*
	0.008	0.006	0.001
Upper Income	0.01	-0.016*	-0.001
	0.007	0.007	0.001
Cars per Household	0.037***	-0.054***	0.006***
	0.008	0.008	0.001
% Not Working	-0.365***	0.239***	-0.036***
	0.027	0.023	0.005
Rideshare Trips	0.000***	-0.000**	0.000
	0.000	0.000	0.000
_cons	0.920***	0.218***	0.990***
	0.011	0.010	0.001
N	1,842,231	2,162,331	1,330,271
adj. R-sq	0.094	0.071	0.009

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Appendix C:
Technical Documentation of the Safety Analysis

The Empirical Bayes (EB) method is used to examine the safety impact of Chicago's speed cameras. The analysis looks at 101 speed camera instrumented locations. Changes in the count of crash incidents within 250 meters on either side of the camera on the instrumented road over a three-year period are used as a basis for evaluating safety. The analysis uses a before-after approach and estimates safety on the basis of comparing the after-period crash counts against what would have happened if cameras were not installed at the treated sites. Since most speed cameras in Chicago were installed in 2013 and 2014, the 2010-2012 period is taken as the before treatment period and the 2015-2017 period is used as the post treatment period in this analysis.

The EB method is implemented as follows. First, similarly treatable, but untreated, road segments were identified to assess the safety performance of roadways in safety zones. These sites are used to estimate safety performance functions (SPFs)–regression equations that are used to estimate the number of expected crashes over some specified period given traffic and geometric conditions on the roadways. These sites were selected by first identifying road segments that fell within safety zones in Chicago. Segments with no volume data were removed. Three hundred points were then randomly placed on these road segments. These locations were taken as an initial set of treatable sites. Sites were then matched against treated locations using propensity score matching on the basis of AADT and number of driveways within a 250-meter buffer on either side of the randomly placed point. The process matched 101 locations in this manner. From the pool of unmatched locations, those with AADT in the range of treated sites were added back. This led to a sample 146 sites based on which safety performance functions for the sites could be estimated.

Next, the crash histories for these sites are gathered and prepared along with volume on the instrumented road, roadway characteristics and population density data for each location. The volume data for this analysis comes from the Illinois Department of Transportation's Getting Around Illinois website. Volume data from the analysis period or closest to the analysis period is used in the estimation of the models. This data is then used to estimate SPFs for the before and after periods.

We use a negative binomial generalized linear model is estimated for the SPF. Three separate SPFs were estimated by injury class to model crashes with fatalities or type A injuries, type B injuries, and type C injuries respectively. The variables included in the SPFs are the road's average annual daily traffic, the intersection density within the buffer, and the population density in the census tract that the camera is located. Each SPF also included a time period dummy to capture the effects of other uncontrolled variables such as vehicle technology and weather that may have impacted safety outcomes but are not directly measured. Population density was included as another proxy for exposure as it may indicate potential conflicts with pedestrians and bicyclists. However, it may also offer some level of traffic calming and therefore influence crash outcomes. The expected number of crashes of a given type at a location, μ is expressed as follows, and estimated using a negative-binomial model:

$$ln(\mu) = \beta_0 + \beta_1 P + \beta_2 ln(V) + \beta_3 ln(I) + \beta_4 ln(D) \quad (1)$$

where:

- μ: expected crashes of of a given injury severity (separate models are estimated for KA, B and C injury severity crashes with similar specification)
- P: analysis period, equal to 1, if year 2015-2017, 0 otherwise
- V: the vehicle miles travelled in the buffer over the period of analysis (AADT * #days* Length of segment)
- I: the intersection density within the buffer ($N_{intersections}$/Length of segment)
- D: population density in the census tract
- β: are model parameters unique for each injury type

Once SPFs are estimated, they are then used to compute the expected number of crashes on the 101 treated locations using their volume and roadway characteristics. These estimates provide a base line estimate for how unsafe a particular location is based on its built and traffic characteristics. The treated sites are not used in the estimation of the SPFs as treatments are often influenced by high crash counts.

The safety performance functions were estimated using the R statistical software. The parameters for the three models and their dispersion parameter θ are reported in *Table 3*. Comparison with the restricted Poisson model supports the use of the Negative Binomial model. The variables in the model–VMT, intersection density and population density– were all important predictors for all crash types with higher values for each variable increasing the number of expected crashes. The period effect was significant only for crashes of injury type K and A and suggested that fatality and incapacitating injury crashes increased in the after period.

Figure 2 shows how the model predictions align with the crash data used to estimate the SPF.

Table 3 *Safety performance functions by injury type*

Variable	Parameter	KA injuries	B injuries	C injuries
Intercept	β_0	-6.305***	-3.687**	-4.714***
Period (P)	β_1	0.333**		
Vehicle miles travelled (V) (log)	β_2	0.307**	0.23**	0.267**
Intersection Density (I) (log)	β_3	0.556**	0.545***	0.696***
Population Density (D) (log)	β_4	0.146.	0.178**	0.131*
Dispersion Parameter	θ	2.958	2.424	2.415
Fit Statistics				
N		292	292	292
Null Deviance		356.1	355	373.9
Degrees of freedom (Null model)		291	291	291
Residual Deviance		230.8	314.6	239.2
Degrees of freedom (final model)		287	288	288

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, . $p < 0.10$

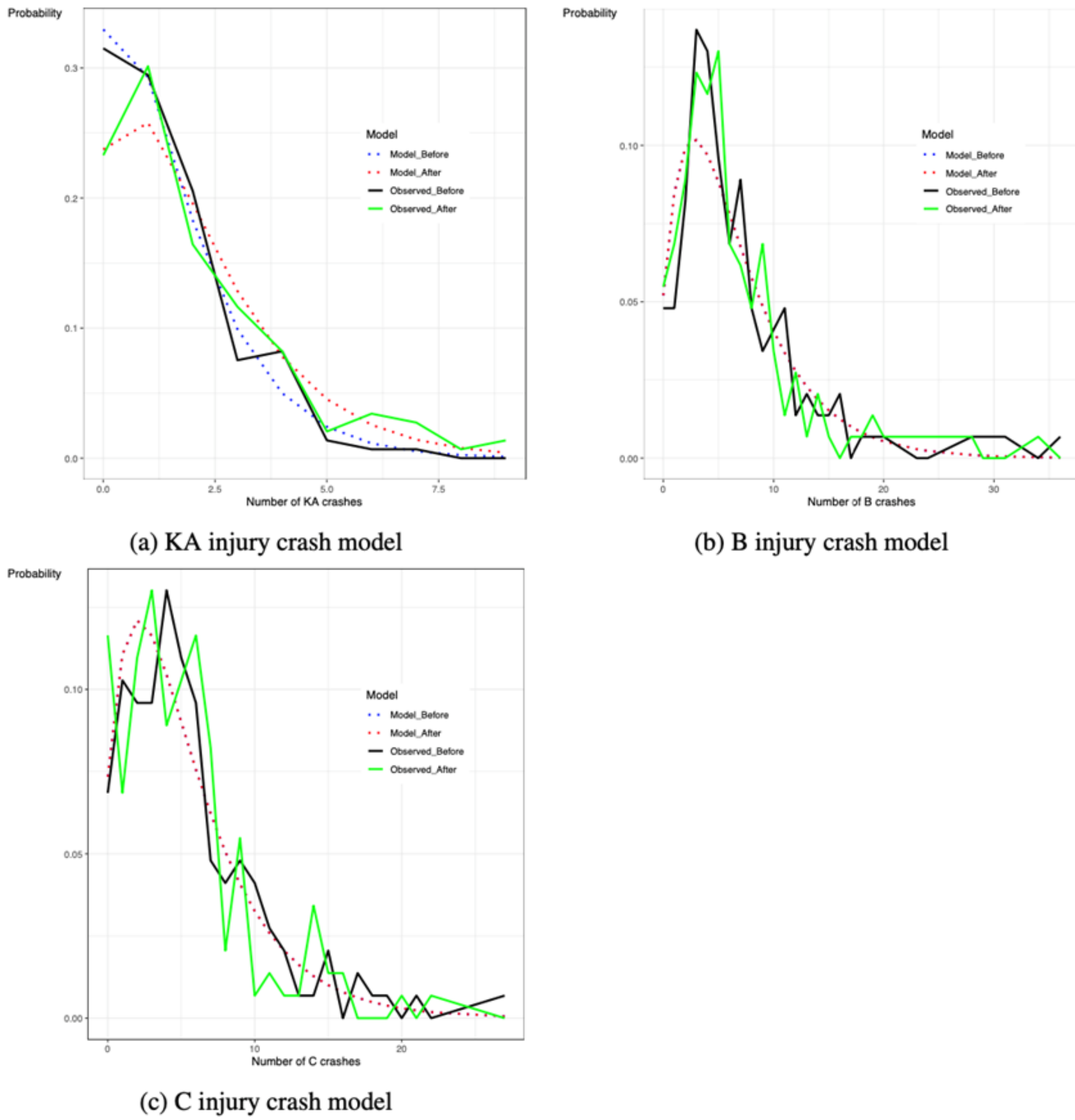


Figure 2 *Safety Performance Function (SPF) predictions compared to crash data. Note that for B and C injury crashes the before and after predictions based on the data are identical since the period variable was not found to be important.*

The Empirical Bayes Approach

In the Empirical Bayes (EB) method, the safety of a given entity is estimated as a weighted sum of the entity's crash record (Y_i) and the estimate of a representative road section with the characteristics matching the entity as estimated by the SPF. Following Hauer,[32] we can write the expected number of crashes for an entity y_i, given its crash record Y_i, as:

$$y_i = \alpha_i \mu_i + (1 - \alpha_i) Y_i \qquad (2)$$

The weight α_i is between 0 and 1, and for a given injury type at a given location can be computed as follows:

$$\alpha_i = \left(1 + \frac{\mu_i}{\theta_i}\right)^{-1} \qquad (3)$$

where θ_i is the ispersion parameter from the estimated SPF for injury type *i* and μ_i is the estimate for the location from the SPF. In this way, the crash estimate from the EB method incorporates information on what we expect to happen for a representative site similar to the site under consideration along the measured attributes, and also adds information about the specific site through the inclusion of the site-specific crash history Y_i.

The estimate y_i in equation 2 provides our best guess as to the safety of an entity in the before period. For treated sites, the crash count in the after period had the site not been treated cannot be observed and is hence unknown. Hauer (1997) offers a way to estimate yi in the after period. We first estimating μ_i in the after period ($\mu_{i,a}$) using the conditions (P, *V*, *I*, *D*) on the treated sites in the after period utilizing our SPFs. To get these estimates, we set *P=1* and the VMT (V) is set the to after-period VMT at each location. The after-period volumes come from traffic counts made by each speed camera. A correction factor to estimate the number of crashes in the after period is then computed as follows:

$$C_i = \frac{\mu_{i,a}}{\mu_{i,b}} \qquad (4)$$

The crash count estimate in the after period for a location $y_{i,a}$ is then computed as follows:

$$y_{i,a} = C_i y_{i,b} \qquad (5)$$

and its variance is computed as:

$$\mathrm{var}(y_{i,a}) = C_i^2(1 - \alpha_i)y_{i,b} \qquad (6)$$

where the subscripts *a* and *b* designate the before and after periods respectively.

The next step is to compute the estimated safety impact of the treatment, which is achieved by comparing our estimate of safety in the after period with (measured by the entities crash record K_i) and what we would have expected to happen had the treatment not been deployed $y_{i,a}$. The safety of impact at each location for crash severity *i* is then:

$$\delta_i = y_{i,a} - K_i \qquad (7)$$

Along with this estimate of safety improvement, the variance is also computed as $var(\delta_i) = var(y_{i,a}) + var(K_i)$, which will allow us to build confidence intervals for the safety impact at each location.

Safety impacts across the analyzed locations can also be summed to offer an overall picture of the effectiveness of speeding cameras. If we use K_t to represent the sum of all crashes across all analysis locations and $y_{t,a}$ as the total of the estimated after period no-treatment crash estimate, the collision reduction ϕ is computed as follows:

$$\phi = \frac{K_t / y_{t,a}}{1 + var(y_{t,a})/y_{t,a}^2} \qquad (8)$$

and its variance is computed as:

$$var(\phi) = \phi^2 \frac{(var(K_t)/K_t^2 + var(y_{t,a})/y_{t,a}^2)}{(1 + var(y_{t,a})/y_{t,a}^2)^2} \qquad (9)$$

The variance of $y_{t,a}$ in the above equation is the sum of the site specific variances given in equation 6.

In this way, the approach allows us to estimate the safety impact of speed cameras at specific locations as well as on aggregate across all locations considered. We can then examine if speed cameras may not be delivering on their promise at specific locations while being effective on aggregate or vice versa. The separate analysis of crashes by injury severity also allows for different degrees of effectiveness for the cameras in counteracting crashes of different severity.

The site level estimates of crash counts in the before and after periods as well as the expected number of crashes of injury type for the 2015-2017 period had the cameras not been installed is provided in *Table 4* below. The table also shows the estimated safety benefits at each location.

Table 4 *Site level crash counts and estimates of improvement in the after-treatment period*

Camera ID	Crash count 2010-2012			Crash count 2015-2017			Expected crashes 2015-2017 if cameras were not installed			Variance of expected crashes 2015-2017 if cameras were not installed			Safety improvement (Negative numbers indicate improvement)		
	Fatality or A injury crashes	B injury crashes	C injury crashes	Fatality or A injury crashes	B injury crashes	C injury crashes	Fatality or A injury crashes	B injury crashes	C injury crashes	Fatality or A injury crashes	B injury crashes	C injury crashes	Fatality or A injury crashes	B injury crashes	C injury crashes
CHI003	5	11	11	0	7	6	3.6	9.5	9.3	1.64	6.72	6.47	-3.6	-2.5	-3.3
CHI004	0	3	1	1	2	3	1.0	3.3	1.9	0.32	2.02	1.11	0.0	-1.3	1.1
CHI005	0	1	1	0	4	2	1.5	2.7	2.6	0.74	2.13	2.00	-1.5	1.3	-0.6
CHI007	4	13	5	1	13	15	2.9	11.0	4.9	1.24	7.83	3.24	-1.9	2.0	10.1
CHI008	1	4	2	2	3	5	1.2	4.0	2.5	0.38	2.51	1.40	0.8	-1.0	2.5
CHI009	1	2	6	4	10	2	1.3	2.8	4.9	0.46	1.80	2.84	2.7	7.2	-2.9
CHI010	1	8	3	1	4	0	1.4	6.7	3.2	0.46	4.27	1.95	-0.4	-2.7	-3.2
CHI013	2	2	3	1	4	1	1.8	3.1	3.7	0.69	2.19	2.46	-0.8	0.9	-2.7
CHI014	0	0	0	0	0	0	0.7	1.3	1.0	0.16	0.65	0.43	-0.7	-1.3	-1.0
CHI015	0	0	2	0	1	1	1.1	1.7	2.8	0.43	1.14	1.82	-1.1	-0.7	-1.8
CHI019	5	9	6	4	5	6	3.7	8.0	5.7	1.73	5.56	3.84	0.3	-3.0	0.3
CHI021	0	0	0	0	1	0	0.6	1.2	0.9	0.13	0.56	0.37	-0.6	-0.2	-0.9

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	Fatality or A injury crashes	B injury crashes	C injury crashes	Fatality or A injury crashes	B injury crashes	C injury crashes	Fatality or A injury crashes	B injury crashes	C injury crashes	Fatality or A injury crashes	B injury crashes	C injury crashes	Fatality or A injury crashes	B injury crashes	C injury crashes
CHI022	5	15	5	3	7	9	3.5	13.5	5.5	1.50	10.42	4.10	-0.5	-6.5	3.5
CHI024	3	17	11	6	13	11	3.3	14.9	9.9	1.83	11.50	7.29	2.7	-1.9	1.1
CHI025	3	7	7	2	2	2	3.0	7.0	6.8	1.47	5.24	4.84	-1.0	-5.0	-4.8
CHI026	3	8	14	7	18	10	3.1	8.0	11.8	1.56	6.18	8.54	3.9	10.0	-1.8
CHI028	1	4	8	4	7	4	1.8	4.5	7.0	0.84	3.18	4.76	2.2	2.5	-3.0
CHI029	1	2	0	1	0	1	1.5	2.8	1.5	0.53	1.82	0.88	-0.5	-2.8	-0.5
CHI030	2	19	21	0	11	2	2.5	15.8	16.4	1.23	11.61	11.55	-2.5	-4.8	-14.4
CHI032	0	3	8	2	4	2	1.5	4.1	7.5	0.73	3.04	5.37	0.5	-0.1	-5.5
CHI034	4	16	14	4	9	11	4.0	14.8	12.7	2.26	11.94	9.75	0.0	-5.8	-1.7
CHI035	2	20	16	4	16	10	2.5	17.6	14.3	1.27	13.86	11.10	1.5	-1.6	-4.3
CHI039	4	11	13	3	5	12	4.2	11.4	12.7	2.50	9.61	10.42	-1.2	-6.4	-0.7
CHI041	2	7	8	1	7	7	3.0	7.8	8.4	1.81	6.41	6.78	-2.0	-0.8	-1.4
CHI043	0	4	3	0	4	1	1.3	4.7	3.7	0.55	3.48	2.50	-1.3	-0.7	-2.7

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CHI044	5	26	21	2	17	21	4.1	21.7	16.9	2.11	16.60	12.19	-2.1	-4.7	4.1
CHI045	0	4	5	0	1	1	1.5	5.0	5.6	0.74	3.95	4.24	-1.5	-4.0	-4.6
CHI048	2	3	10	2	2	9	2.1	3.8	8.3	0.90	2.62	5.55	-0.1	-1.8	0.7
CHI049	0	8	4	1	4	1	1.4	7.8	4.5	0.64	5.82	3.17	-0.4	-3.8	-3.5
CHI050	0	12	5	2	4	2	1.4	10.5	5.0	0.62	7.65	3.39	0.6	-6.5	-3.0
CHI051	2	19	6	2	9	12	2.6	16.6	6.1	1.32	12.79	4.49	-0.6	-7.6	5.9
CHI055	6	13	19	1	12	9	5.3	13.2	17.9	3.11	11.33	14.90	-4.3	-1.2	-8.9
CHI056	0	2	8	1	8	3	1.3	3.2	7.2	0.59	2.38	4.99	-0.3	4.8	-4.2
CHI057	1	10	8	2	11	10	2.4	9.9	8.0	1.41	7.89	6.18	-0.4	1.1	2.0
CHI058	0	1	0	0	1	0	0.8	1.9	1.2	0.22	1.06	0.60	-0.8	-0.9	-1.2
CHI059	3	23	22	5	23	24	3.0	19.4	17.5	1.51	14.74	12.52	2.0	3.6	6.5
CHI062	1	3	3	0	5	2	2.0	4.0	3.8	0.98	2.90	2.68	-2.0	1.0	-1.8
CHI063	3	19	4	0	6	8	2.6	15.1	4.3	1.10	10.65	2.88	-2.6	-9.1	3.7

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CHI064	0	4	3	0	3	0	1.1	4.1	3.2	0.40	2.56	1.87	-1.1	-1.1	-3.2
CHI066	1	3	4	0	5	0	1.9	4.1	4.6	0.94	3.06	3.31	-1.9	0.9	-4.6
CHI068	4	18	12	2	12	15	4.1	17.3	11.9	2.40	14.68	9.80	-2.1	-5.3	3.1
CHI070	1	0	4	2	5	2	2.0	1.9	4.7	0.98	1.45	3.50	0.0	3.1	-2.7
CHI071	3	18	23	5	15	6	2.7	14.3	16.6	1.19	9.98	10.81	2.3	0.7	-10.6
CHI074	2	6	5	1	5	3	2.2	5.9	4.9	1.02	4.18	3.28	-1.2	-0.9	-1.9
CHI075	7	7	8	1	19	6	5.4	7.5	8.1	2.94	5.91	6.23	-4.4	11.5	-2.1
CHI077	0	7	1	1	5	8	1.5	7.2	2.5	0.76	5.49	1.85	-0.5	-2.2	5.5
CHI078	1	8	6	0	7	7	2.0	7.9	6.1	0.99	6.06	4.45	-2.0	-0.9	0.9
CHI080	3	7	4	2	2	0	3.4	7.5	4.9	1.96	5.96	3.78	-1.4	-5.5	-4.9
CHI083	1	3	9	3	7	4	2.1	4.1	8.2	1.08	3.07	5.89	0.9	2.9	-4.2
CHI086	4	3	9	0	11	4	3.9	4.4	8.9	2.24	3.53	6.94	-3.9	6.6	-4.9
CHI087	3	8	14	3	9	9	3.0	7.9	11.9	1.48	5.93	8.56	0.0	1.1	-2.9

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	Fatality or A injury crashes	B injury crashes	C injury crashes	Fatality or A injury crashes	B injury crashes	C injury crashes	Fatality or A injury crashes	B injury crashes	C injury crashes	Fatality or A injury crashes	B injury crashes	C injury crashes	Fatality or A injury crashes	B injury crashes	C injury crashes
CHI090	0	5	5	2	5	4	1.2	5.1	4.7	0.49	3.54	3.03	0.8	-0.1	-0.7
CHI093	4	16	17	3	10	14	3.8	14.4	14.4	2.13	11.27	10.70	-0.8	-4.4	-0.4
CHI095	3	7	4	1	8	2	2.8	7.0	4.5	1.32	5.20	3.18	-1.8	1.0	-2.5
CHI097	2	9	12	3	5	9	2.2	8.4	10.1	1.00	6.23	7.07	0.8	-3.4	-1.1
CHI098	8	11	9	2	11	7	6.0	10.9	8.9	3.24	8.85	6.95	-4.0	0.1	-1.9
CHI100	2	5	2	2	10	4	2.2	5.3	3.0	0.96	3.85	2.09	-0.2	4.7	1.0
CHI101	5	6	6	1	9	10	3.6	6.4	6.0	1.64	4.79	4.26	-2.6	2.6	4.0
CHI102	2	4	3	1	6	5	2.0	4.3	3.4	0.79	2.89	2.12	-1.0	1.7	1.6
CHI103	0	3	4	3	5	3	1.5	4.2	4.8	0.77	3.24	3.53	1.5	0.8	-1.8
CHI104	2	8	11	2	6	8	2.5	7.7	9.4	1.22	5.69	6.62	-0.5	-1.7	-1.4
CHI106	2	8	3	5	8	4	2.7	8.3	4.2	1.46	6.60	3.21	2.3	-0.3	-0.2
CHI107	3	22	9	4	9	14	3.1	19.1	8.7	1.65	14.94	6.59	0.9	-10.1	5.3
CHI109	0	8	2	4	4	5	1.6	8.4	3.5	0.83	6.81	2.74	2.4	-4.4	1.5

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CHI110	2	11	8	6	18	9	1.9	8.9	6.5	0.77	5.96	4.05	4.1	9.1	2.5
CHI112	4	11	10	2	12	8	2.9	9.0	7.9	1.25	6.07	5.07	-0.9	3.0	0.1
CHI114	0	5	3	3	5	4	1.1	4.8	3.2	0.41	3.17	1.94	1.9	0.2	0.8
CHI115	1	8	9	1	1	3	2.1	8.0	8.5	1.15	6.11	6.32	-1.1	-7.0	-5.5
CHI117	2	7	4	0	7	3	1.8	6.4	4.0	0.69	4.35	2.51	-1.8	0.6	-1.0
CHI118	1	4	1	2	5	5	1.3	4.2	2.0	0.44	2.68	1.21	0.7	0.8	3.0
CHI119	1	2	3	3	2	1	1.8	3.1	3.6	0.82	2.15	2.43	1.2	-1.1	-2.6
CHI120	2	3	3	1	2	1	2.2	3.9	3.9	0.96	2.85	2.78	-1.2	-1.9	-2.9
CHI122	1	5	7	0	5	2	1.6	5.1	6.1	0.62	3.46	3.90	-1.6	-0.1	-4.1
CHI123	5	9	7	2	6	11	4.3	9.0	7.3	2.35	7.16	5.65	-2.3	-3.0	3.7
CHI124	2	12	8	7	16	10	3.0	11.6	8.2	1.77	9.32	6.49	4.0	4.4	1.8
CHI126	3	3	5	2	4	7	3.7	5.2	7.1	2.27	4.93	6.76	-1.7	-1.2	-0.1
CHI127	3	13	10	6	7	6	2.9	11.3	8.6	1.43	8.29	5.97	3.1	-4.3	-2.6

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CHI129	0	7	5	2	2	1	1.2	6.9	4.9	0.52	5.04	3.30	0.8	-4.9	-3.9
CHI133	3	14	16	6	16	10	3.3	12.5	13.2	1.81	9.54	9.42	2.7	3.5	-3.2
CHI134	1	5	10	3	3	11	2.1	5.9	9.3	1.07	4.64	6.96	0.9	-2.9	1.7
CHI136	0	8	1	0	2	5	1.4	7.8	2.5	0.71	5.90	1.81	-1.4	-5.8	2.5
CHI138	0	4	1	1	0	1	1.5	5.4	2.8	0.80	4.54	2.30	-0.5	-5.4	-1.8
CHI140	4	6	6	0	11	5	3.2	6.1	5.9	1.50	4.38	4.08	-3.2	4.9	-0.9
CHI142	1	6	1	0	2	3	1.9	6.6	2.6	0.95	5.16	1.94	-1.9	-4.6	0.4
CHI143	1	2	7	2	7	6	1.7	3.2	6.3	0.74	2.32	4.16	0.3	3.8	-0.3
CHI144	1	5	1	0	10	5	1.7	5.0	2.2	0.72	3.40	1.38	-1.7	5.0	2.8
CHI145	5	10	7	0	6	3	3.5	8.8	6.4	1.51	6.24	4.31	-3.5	-2.8	-3.4
CHI146	0	6	8	2	8	6	1.3	6.4	7.7	0.58	4.90	5.67	0.7	1.6	-1.7
CHI147	1	15	10	5	8	12	2.4	14.9	10.4	1.51	12.74	8.78	2.6	-6.9	1.6
CHI148	3	23	14	2	23	7	2.4	18.8	11.5	0.99	13.87	8.08	-0.4	4.2	-4.5

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CHI149	1	2	0	1	1	1	2.2	3.4	1.8	1.23	2.65	1.36	-1.2	-2.4	-0.8
CHI156	1	3	2	3	5	4	1.6	3.7	2.8	0.61	2.50	1.77	1.4	1.3	1.2
CHI158	2	2	3	0	2	2	1.6	2.7	3.0	0.52	1.66	1.70	-1.6	-0.7	-1.0
CHI160	4	14	14	12	20	17	3.4	12.5	12.2	1.71	9.56	9.06	8.6	7.5	4.8
CHI162	6	1	3	0	6	2	4.2	2.5	3.8	1.95	1.86	2.72	-4.2	3.5	-1.8
CHI164	5	6	9	2	13	5	4.2	7.1	9.1	2.24	5.91	7.23	-2.2	5.9	-4.1
CHI165	2	5	6	1	3	5	2.6	5.5	6.1	1.32	4.13	4.48	-1.6	-2.5	-1.1
CHI167	2	7	14	2	3	9	2.6	7.2	12.1	1.36	5.52	8.89	-0.6	-4.2	-3.1
CHI168	1	17	13	3	11	12	1.6	13.5	9.9	0.66	9.42	6.42	1.4	-2.5	2.1
CHI170	0	3	3	0	5	3	1.4	4.0	3.8	0.63	2.89	2.65	-1.4	1.0	-0.8
CHI171	3	23	15	4	13	8	3.6	20.3	13.5	2.15	16.27	10.44	0.4	-7.3	-5.5
All sites	209	820	719	208	731	591	244	799	691	120	603	500	-36	-68	-100

Endnotes

[1] We define Fines and Fees as separate dimensions of monetary sanctions. A Fine is the fixed monetary charge associated with a red-light or speeding infraction determined by an automated enforcement camera, which is currently $100 for red-light camera violations and either $35 or $100 for speeding camera violations, determined based on the driving speed above regulation. Whereas Fees are monetary penalties added to Fines. They may include late or unpaid ticket fees, vehicle immobilization or boot fees, towing and impoundment fees. In this analysis, Fees do not include indirect costs that drivers with numerous unpaid tickets might incur such as license suspension, attorney fees, bankruptcy, and employment disruption.

[2] Pilkington, P. and S. Kinra, Effectiveness of speed cameras in preventing road traffic collisions and related casualties: systematic review. Vol. 330, No. 7487, 2005, pp. 331–24334. Li, H., D. J. Graham, and A. Majumdar, The impacts of speed cameras on road accidents: An application of propensity score matching methods. Accident Analysis & Prevention, Vol. 60, 2013, pp. 148–157. Mountain, L., W. Hirst, and M. Maher, Costing lives or saving lives: a detailed evaluation12of the impact of speed cameras. Traffic, Engineering and Control, Vol. 45, No. 8, 2004,13pp. 280–287.146. Hess, S., Analysis of the effects of speed limit enforcement cameras: Differentiation by road type and catchment area. Transportation research record, Vol. 1865, No. 1, 2004, pp.1628–34.177. Elvik, R., Effects on accidents of automatic speed enforcement in Norway. Transportation Research Record, Vol. 1595, No. 1, 1997, pp. 14–19.198. Thomas, L. J., R. Srinivasan, L. E. Decina, and L. Staplin, Safety effects of automated speed enforcement programs: critical review of international literature. Transportation 21Research Record, Vol. 2078, No. 1, 2008, pp. 117–126.229. Gains, A., B. Heydecker, J. Shrewsbury, and S. Robertson, The national safety camera programme-three year evaluation report, 2004. Wong, Timothy. (2014) "Lights, camera, legal action! The effectiveness of red-light cameras on collisions in Los Angeles." Transportation Research Part A: Policy and Practice, 69: 165-182; Gallagher, J. and Fisher P. (2017) "Criminal Deterrence when there are Offsetting Risks: Traffic Cameras, Vehicular Accidents, and Public Safety." Vehicular Accidents, and Public Safety (November 17)

[3] Maine, Mississippi, New Hampshire, South Carolina, Texas and West Virginia prohibit both red-light and speed cameras. Montana and South Dakota prohibit red-light cameras, and New Jersey and Wisconsin do not allow speed cameras. Nevada prohibits the use of cameras unless operated by an officer or installed in a law enforcement vehicle or facility. National Conference of State Legislatures, Automated Enforcement Overview, https://www.ncsl.org/research/transportation/automated-enforcement-overview.aspx

[4] Insurance Institute for Highway Safety https://www.iihs.org/topics/red-light-running; automated enforcement cameras

[5] National Conference of State Legislatures, Automated Enforcement Overview, https://www.ncsl.org/research/transportation/automated-enforcement-overview.aspx; Teresa Boeckel (June 29, 2020). Speed cameras in Pennsylvania work zones: 30,000 violations issued so far, York Daily Record. https://www.ydr.com/story/news/2020/06/29/speed-cameras-pa-thousands-violations-3-months-enforcement/3263842001/

[6] Lee R. Wickert (June 19, 2019) The Red Light Traffic Camera Controversy https://www.mwl-law.com/the-red-light-traffic-camera-controversy/

[7] Barajas, J. (2020) "Biking While Black: How Planning Contributes to Unjust Policing," TREC Friday Seminar Series. 194. https://archives.pdx.edu/ds/psu/33270; Brazil, N. (2018), "The Unequal Spatial Distribution of City Government Fines: The Case of Parking Tickets in Los Angeles." Urban Review; Chicago Metropolitan Agency for Planning (April 2021) Improving equity in transportation fees, fines, and fares Findings and recommendations for northeastern Illinois; Pattillo, M. and Kirk, G. (2020) Pay Unto Caesar: Breaches of Justice in the Monetary Sanctions Regime. UCLA Criminal Justice Law Review, 4(1), 49–77; Sanchez, M. (2018) ProPublica Illinois and WBEZ Driven into Debt series; The Chicago Fines, Fees & Access Collaborative; Woodstock Institute (June 2018) *The Debt Spiral: How Chicago's Vehicle Ticketing Practices Unfairly Burden Low-Income and Minority Communities.*

[8] Vera Institute (August 2021) Investing in Evidence-Based Alternatives to Policing: Non-Police Responses to Traffic Safety https://www.vera.org/downloads/publications/alternatives-to-policing-traffic-enforcement-fact-sheet.pdf; Justin Fox. One tool to cut racism in policing: Traffic cameras. Bloomberg Opinion, July 2020.

[9] Mello, S. (2018). Speed trap or poverty trap? Fines, fees, and financial wellbeing. Work. Pap., FFJC, New York. Kathryn Zickuhr (April 22, 2019) "Applying a racial equity lens to fines and fees in the District of Columbia"

[10] City of Chicago Automated Enforcement Program, 2019 Annual Report

[11] The hours of enforcement for these cameras depends on whether the camera is installed in a school or a park Safety Zone. School cameras operate from 7 a.m. to 7p.m. on school days, while park cameras operate every day from 6 a.m. to 11 p.m.

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