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Ticket to Abide: The Role of Implicit Bias in Chicago Parking Ticket Distribution

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Ticket to Abide:

The Role of Implicit Racial Bias in Chicago Parking Ticket

Distribution

Satisfying the Requirements for Honors in Management

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May 2019

Abstract
A recent rise in media attention regarding police discrimination towards minorities has brought the pervasiveness of biases to the forefront of the public's attention. In the last decade alone, countless studies have sought to expand our understanding of the presence of discrimination in police behavior through detailed analyses of profiling, traffic stops, jury systems, and other key policies. The continued confirmation of these discrepancies in behavior and their resulting outcomes inspired a further analysis of their effects on the distribution of parking tickets. We sought to examine whether this discrimination is a result of peripheral racial biases in which police officers rely on their heuristics of racial minorities to inform their actions. Since officers do not interact face-to-face with offenders when issuing parking tickets, is this behavior indicative of implicit bias?

To better answer this question, we performed a difference-in-differences analysis of parking ticket distribution in the city of Chicago spanning the last decade between minority and White police officers based on the districts they patrol. Using a fixed effects linear model, we isolated police bias in ticketing behavior and concluded that there was no clear trend of racial discrimination across the police force. However, trends did exist highlighting lenient ticketing behavior in majority white areas and clear distinctions about how White officers issue tickets along racial lines.

I. Introduction

While the debate surrounding racial bias and its implications for our society is not limited to police behavior, stories detailing irregularities in the execution of standard police duties such as traffic stops, stop-and-frisk, and arrests have become increasingly prominent in news cycles. Recent studies of traffic stops, drug wars, police profiling, and jury selection have attempted to analyze this discrimination in an attempt to understand the proliferation, nature, and extent to which biases exist amongst officers' behavior. Particularly intriguing is the role of racial profiling in discrepancies of police behavior towards the general population. In the book *Suspect Citizens*, Baumgartner, Epp, and Shoub examined 20 million traffic stops and discovered that "Blacks are almost twice as likely to be pulled over as whites- even though whites drive more on average" and " just by getting in a car, a black driver has about twice the odds of being pulled over and almost four times the odds of being searched" (Baumgartner, Epp, & Shoub, 2018). Their research was furthered by a U.S. Department of Justice examination which noted that Black residents were more likely to be stopped by police than White or Hispanic residents, both in traffic stops and street stops (Davis, Whyde, & Langton, 2018). Data on stop-and-frisk programs as well as traffic stops have been heavily examined by a number of scholars and consistently show results in line with conclusions of the study by Baumgartner, Epp, and Shoub (Baumgartner, Epp, & Shoub, 2018). These powerful findings initiated our personal curiosity in the role and extent of implicit racial biases in all forms of ticketing behavior.

ProPublica Illinois, in partnership with the radio station WBEZ, recently published a dataset of the City of Chicago parking ticket distribution that included both the unique badge identification numbers belonging to the officers providing the tickets in addition to relevant information on the ticket itself: location, vehicle type, violation, etc (ProPublica Illinois &

WBEZ, 2018). This presented an interesting nuance to recent research on racial bias and profiling; with a parking ticket, officers typically do not see the owner of the vehicle themselves so any potential bias would stem from stereotypes, heuristics, and implicit biases based on the vehicle type and location. We took this opportunity to try to isolate the possibility of implicit biases present in the act of giving out parking tickets. Chicago served as the primary target for our research both because of the availability of this data as well as Chicago's position as one of the most segregated cities in America, which enhanced the precision of tracking variability in behavior.

Officers are assigned to specific zones referred to as "beats" in groups of approximately 9 to 10 people which they patrol for approximately a year (Chicago Police Department, 2017). Beats are designed to help build trust within a community based on the idea that a police officer who regularly patrols the same area for upwards of a couple of months will better integrate into communities and become a more trusted resource which will, in turn, help reduce crime (Brown & Wycoff, 1987). These beats generally cover several zip codes, and the zone a police officer is patrolling can vary significantly in racial makeup, crime rates, and income as zip codes in Chicago have vastly different demographics. As a result, an individual officer, in their beat, will experience significant variation in their day-to-day or week-to-week routines. This was critical for our research because, for a given beat assignment, we are able to track a group of police officers' parking ticket behavior in areas with very different racial composition and analyze this for possible displays of implicit biases by comparing the behavior of the officers in the beat patrol with one another. It is interesting to note that because officers patrol the same area over the course of a year, they are more familiar with the region and thus better able to identify the

factors presented previously: racial composition, wealth, crime levels, etc., which may influence their behavior when distributing tickets.

Below, we provide a map of the current police beats in the city of Chicago; there are a total of 279 beats in Chicago with approximately nine to ten officers assigned per beat (City of Chicago, 2019).

Exhibit 1: Map of Police Officer Beats in Chicago in 2019.
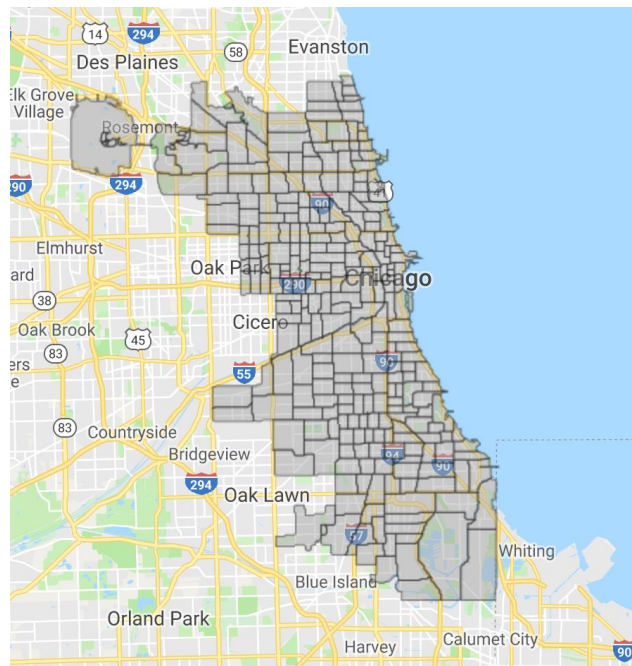
Our goal was to analyze implicit bias by isolating the behavior of officers of different races within the same zip code and to use a difference-in-differences analysis to determine whether their standard behavior significantly diverged from one another along racial lines.

II. Literature Review

ProPublica examined data on Chapter 13 bankruptcies and concluded that an estimated 1,000 bankruptcies included debts to the city in the form of unpaid tickets with a median value of $1,500 (Sanchez & Kambhampati, 2018). Since then, the number of cases has increased by 10x with the median debt owed at $3,900 as the city continues to raise the costs of fines. In particular, Chicago leads the nation in Chapter 13 filings with ticket debt disproportionately affecting those in the city's low-income, mostly Black neighborhoods.

Suspect Citizens (Baumgartner, Epp, & Shoub, 2018) demonstrated, "Blacks are almost twice as likely to be pulled over as whites," and a U.S. Justice Department study (Davis, Whyde, & Langton, 2018) further emphasized, "Black and Latino drivers are more likely to be searched once they have been pulled over". Systematic displays of oppression towards minorities are heavily present in driving and vehicular ownership, and this discrepancy pervades nationwide. Missouri's Attorney General's office reported recently that in 2017, Blacks were 85% more likely to be stopped at traffic stops (Hawley, 2017). In addition, a study of traffic stops by Simoiu, Corbett-Davies, and Goel in North Carolina found Blacks and Latinos more likely to be searched than Whites despite White motorist searches turning up contraband more frequently (Simoiu, Corbett-Davies, & Goel, 2017). Furthermore, similar figures are reported in related studies by the Civil Rights Division of the U.S. Department of Justice completed in Ferguson (United States Department of Justice Civil Rights Division, 2015), revealing that "black people [...] account for 85 percent of vehicle stops, 90 percent of citations and 93 percent of arrests, despite comprising 67 percent of the population." In Kansas City, "blacks were 2.7 times more likely to be pulled over in an investigatory stop, and five times more likely to be searched" (Epp, Maynard-Moody, & Haider-Markel, 2014). Yet another study in Nashville found that "black

drivers were searched at twice the rate of white drivers, though - as in other jurisdictions - searches of white drivers were more likely to turn up contraband" (Gideon's Army, 2016). For the purpose of our research, we focused on literature related to discrimination occurring in situations related to vehicles or driving, but evidence of bias in police behavior extends beyond these key areas and includes but is not limited to the drug war (Benner, 2002), misdemeanors (Stevenson & Mayson, 2018), and stop-and-frisk scenarios (Fryer, Jr, 2016).

While not all of this research pertains to parking tickets, these reports' representation of the prevalence of discrimination by officers indicates greater structural issues. These issues are likely manifested in other displays of officer behavior. Implicit biases leading to highly discriminatory behavior are rarely limited to one situation and form the foundation for our analysis of parking ticket discrimination. The rising debt reported by ProPublica further corroborates this belief (Sanchez & Kambhampati, 2018). However, while evidence exists of disproportionate debt accumulation due to parking tickets, there has been little research thus far attempting to unearth the presence of clear implicit biases displayed by officers of different races exemplified through patterns of parking ticket distribution. We seek to add to existing literature that has sought to understand the presence of officer behavior bias by analyzing its presence, in the context of parking tickets, within a city where crippling parking ticket debt is heavily taxing its minority populations.

III. Hypothesis

We hypothesized that White police officers would have a higher likelihood of issuing a parking ticket in a low-income, predominantly minority neighborhood. In addition, we predicted

that police officers would give fewer tickets in areas where their race is the majority, i.e., a Black officer will issue the fewest tickets in a majority Black area.

Parking tickets work differently from other traffic violations because they must be given solely based on an officer's judgment of the car and location rather than the driver's behavior or appearance. Systematic bias in traffic control has been abundantly addressed in research; however, we seek to further this research by examining the unconscious biases that may be apparent in parking ticket distribution due to the inherently unique nature of the ticket itself, i.e., no interaction with the owner/driver of the vehicle. We believe that White officers in neighborhoods with higher minority representation may change their behavior in comparison to their minority officer counterparts, which will ultimately reveal an increase in the likelihood of receiving a ticket based on the race of officers and thus provide concrete evidence of the impact of implicit biases.

We are comparing the behavior of White, Black, Hispanic and Asian officers patrolling beats together to one another. We believe that officers of minority groups will be least likely to give tickets to areas dominated by their respective minority groups.

IV. Data

The majority of the data used in our research is from the Chicago Department of Finance in collaboration with ProPublica Illinois. This dataset contains information on all of the parking and vehicle compliance tickets issued in Chicago from January 2007 through May 2018. Within this dataset is information about when, where, and by whom the tickets were issued. While further information was available about the ticket itself, we focused primarily on these three principal factors. The data included unique badge ID numbers that could be matched with

individual Chicago officers and used to trace their parking ticket distribution while they were active during this timeframe. Publicly, this data did not include the officer names so, in connection with the Chicago Police Department, we gathered a corresponding dataset through a Freedom of Information Act (FOIA) request that allowed us to match the names of officers with their badge IDs. However, this data merely provided their names and did not include key demographic information, such as race.

In order to estimate the likely race of officers, we used a validated algorithm that predicts the race of a person based on their first name by analyzing the statistical probability of a race based on data from mortgage applications (Tzioumis, 2018). Using linked name and race data from mortgage loan applications, the algorithm calculates a percentage likelihood that a particular name for a person is linked to a given race. Six races were used: Black, White, Asian, Hispanic, American Indian/Pacific Islander/Alaska Native, and two or more races. Due to the absence of officers identified as American Indian/Pacific Islander/Alaska Native or two or more races according to this algorithm, we omitted these categories from our analysis. We applied the algorithm to the names of the Chicago police officers in our dataset in order to calculate the likelihood of each individual belonging to each of the aforementioned races. We then assigned each officer to a race based on which statistical probability was highest. With the race assignment complete, we were able to attach the name and predicted race of an officer with each of the tickets they gave out between 2007 and 2018.

The next step was gathering zip code-level demographic information. We gathered data from 58 zip codes in the Chicago area regarding their racial composition, population, income levels, and crime rates. Population information was taken from the United States Census Bureau 2017 American Community Survey, which included population estimates of each race by zip

code from 2011 to 2017 (US Census Bureau, 2017). Income information was also taken from the

US Census Bureau using the 2013-2017 American Community Survey 5-Year Estimates and

extended from 2009 to 2017 (US Census Bureau, 2017). We used median income to account for

average income by zip code. An example of the racial composition of the zip codes we examined

in Chicago in 2017 can be seen below.

Exhibit 2: Racial Composition by Zip Code in Chicago in 2017. Darkest colors refer to the

highest presence of the title race for each image.
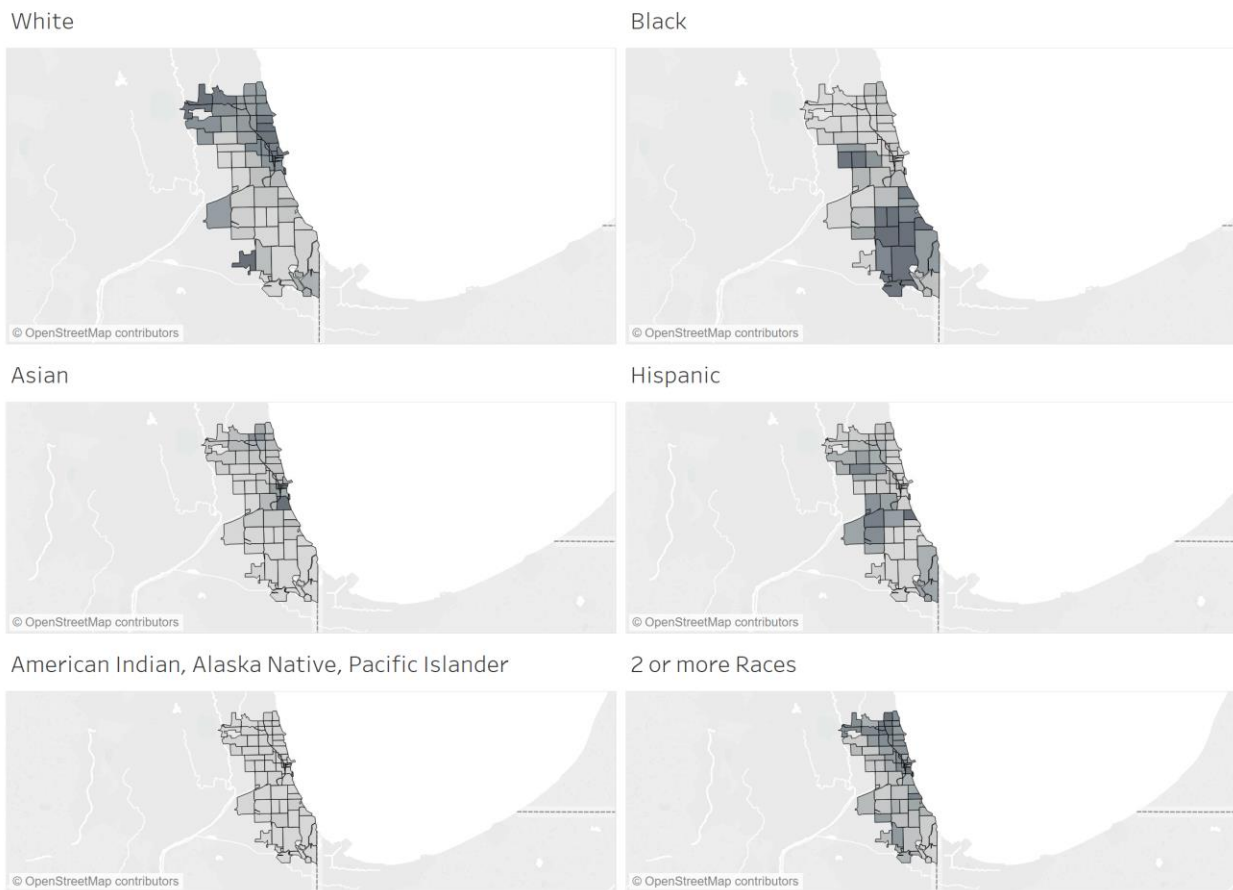
We conducted an estimate of the violent crime rates in each of the zip codes using data

published on the Chicago city website (Chicago Police Department, 2019). This dataset includes

"reported incidents of crime [...] that occurred in the City of Chicago from 2001 to present." We downloaded the data by each zip code and then classified each type of crime as violent or non-violent based on what we believed classified under the definition of violent crime: behaviors by persons, against persons or property that intentionally threatens, attempts, or actually inflicts harm. According to US legal definitions, this includes but is not limited to "aggravated assault, arson, [...] battery, domestic violence, hate crimes, homicide, manslaughter [...]" (USLegal, Inc., 2016).

Violent	Non-Violent
Arson Assault Battery Criminal Sexual Assault Homicide Kidnapping Offense involving Children Robbery Sex Offense	Burglary Concealed Carry License Violation Criminal Damage Criminal Trespass Deceptive Practice Gambling Interference with Public Officer Intimidation Liquor License Violation Motor Vehicle Theft Narcotics Non-Criminal Obscenity Other Narcotic Violation Other Offence Prostitution Public Indecency Public Peace Violation Stalking Theft Weapons Violation

We used violent crime for our research because it creates a more negative perception of an area, which we believe influences officers' perspective. Additionally, violent crime is a common standard for reporting crime rates, especially in Chicago. We used a formula from the Office of the Attorney General in California in which crime rate is calculated by dividing the number of reported crimes by the total population in a given zip code and then multiplying by 100,000 (Office of the Attorney General, n.d.). Using this system, we were able to generate an

overview of the most violent zip codes in Chicago. The graphic below shows the crime rates during the year 2017 by zip code.

Exhibit 3: Violent Crime Rate by Zip Code in Chicago in 2017. Darkest colors correspond to highest crime rate.
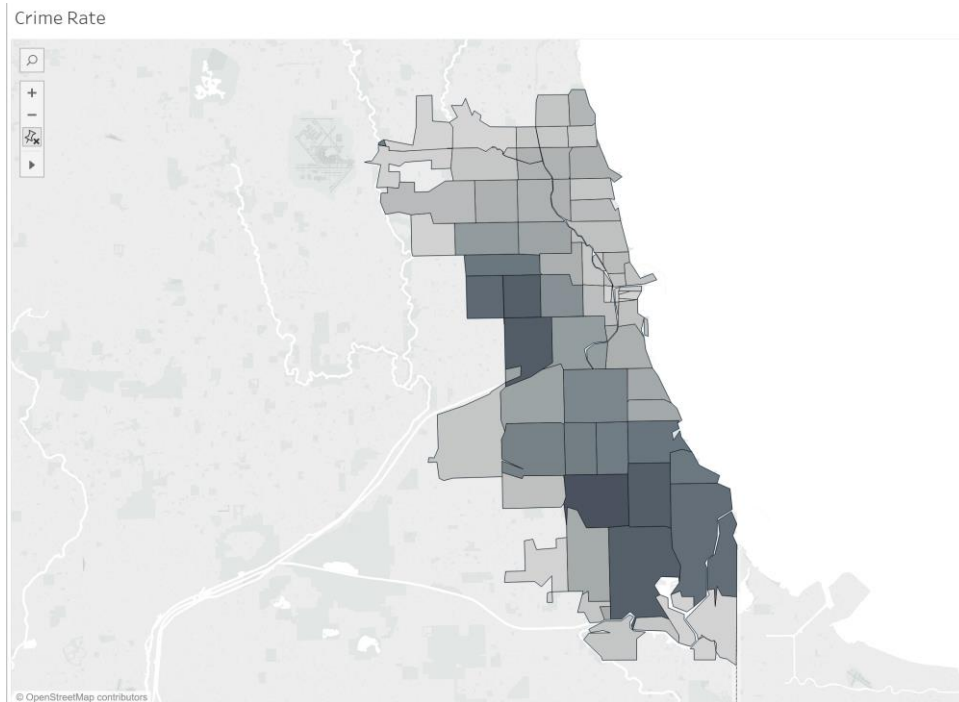
Summary Statistics

Ultimately our data consisted of tickets issued between 2007 and 2018 and encompassed a total of 58 zip codes. After cleaning the data, we included a total of 9,333 officers in our study with 7,938 White officers, 100 Black officers, 1,258 Hispanic officers, and 45 Asian officers. In total, 3,035,833 tickets were issued with 2,648,929 by White officers, 21,678 by Black officers, 355,818 by Hispanic officers, and 12,183 by Asian officers.

V. Methodology

We conducted a difference-in-difference analysis in order to assess our research question. First, we took the following steps to clean our data and eliminate external variable bias in all tickets given:

A. We first combined our parking ticket data with our police officer data by matching the officer badge number attached to each ticket with officer names, excluding those that didn't match. We then matched each police officer's name with our database of names and likely races, removing police officers and their corresponding tickets that didn't have likely race data.

B. Once we had tickets matched with the likely race of the ticketing officer, we mapped the zip code each ticket was issued in with zip code-level demographic information, including crime rate, median income, and racial profile. By adding these variables, we could control for zip code fixed effects when building our difference-in-differences regression.

C. Once we compiled this information, we noticed no officers were assigned into the American Indian, Alaska Native, Pacific Islander, or multiracial categories, so we removed those labels from our analysis of police officers. Similarly, when running some initial tests of our regression, we noticed very low percentages of those racial profiles in zip codes, giving skewed results, so we combined these with percent Asian, the next smallest racial group, when examining zip code racial profile.

D. To determine which police officers to remove that wouldn't be suitable to include in the difference-in-differences, we next transformed the data with each row corresponding to the number of tickets an officer gave in a specific zip code in a specific week, looking at

all officers in all zip codes they patrolled and in every week they gave tickets. We

removed officers who only gave tickets in one zip code over the course of their entire

career since we could not track the difference in their ticketing behavior.

E. We defined an officer's career in a zip code as starting when they gave their first ticket in

a particular zip code and ending when they gave their last ticket in the zip code. This

way, we could fill in all weeks that the officer didn't give tickets in their zip code and add

a row specifying zero tickets for each week in between. This meant that our model

captured police behavior with greater accuracy.

This allowed us to create the regression model to determine the impact of race on

ticketing behavior. Our dependent variable was the number of tickets given by an officer in a zip

code in a week. We ran a difference-in-differences regression, taking into account officer, week,

and zip code fixed effects to control for variation along those aspects of the data. Our model was:

$$Y_{owz} = B_0 + B_1(r_1 * d_1)_{owz} + B_2(r_1 * d_2)_{owz} + B_3(r_1 * d_3)_{owz} + B_4(r_1 * d_4)_{owz} + B_5(r_1 * d_5)_{owz} +)_{owz} + B_6(r_1 * d_6)_{owz} + B_7(r_2 * d_1)_{owz} + B_8(r_2 * d_2)_{owz} + B_9(r_2 * d_3)_{owz} + B_{10}(r_2 * d_4)_{owz} + B_{11}(r_2 * d_5)_{owz} + B_{12}(r_2 * d_6)_{owz} + B_{13}(r_3 * d_1)_{owz} + B_{14}(r_3 * d_2)_{owz} + B_{15}(r_3 * d_3)_{owz} + B_{16}(r_3 * d_4)_{owz} + B_{17}(r_3 * d_5)_{owz} + B_{18}(r_3 * d_6)_{owz} + officer_o + week_w + zip_z + e_{owz},$$

where Y = number of tickets given by an officer in a zip code in a week, r = race of police officer

(1 = White, 2 = Black, 3 = Hispanic), d = zip code demographic (1 = percentage White, 2 =

percentage Black, 3 = percentage Hispanic, 4 = percentage Asian/other, 5 = crime rate, 6 =

median income), officer = officer fixed effects, week = week fixed effects, and zip = zip code

fixed effects. Since we used interaction terms to pair race of police officer with zip code

demographics, to avoid collinearity, we omitted Asian officers in our regression equation, using

Asian officers in Asian/other zip codes as our reference group. We used this benchmark since it

was the least computationally intensive.

VI. Results

Table 1: Change in Tickets for One Unit Increase in Demographic Variable

	White zip	Black zip	Hispanic zip	Asian/other zip	Crime rate	Median income
White	-0.065 (<0.001)	-0.026 (0.021)	0.022 (0.027)	-0.045 (0.028)	0.0000055 (<0.001)	0.00000050 (<0.001)
Black	-0.019 (0.297)	0.027 (0.061)	-0.014 (0.281)	-0.033 (0.191)	0.0000020 (0.228)	0.00000078 (<0.001)
Hispanic	-0.075 (<0.001)	-0.018 (0.110)	0.010 (0.344)	-0.060 (0.004)	0.0000044 (0.002)	0.00000096 (<0.001)
Asian	Ref	Ref	Ref	Ref	Ref	Ref

Looking at Table 1, we first read each row individually to compare officer behavior for officers of different races across different zip code characteristics, then we examine each column to see overall trends by zip code demographics. By including fixed effects for officers, weeks, and zip codes in our regression, we can ensure that our findings hold true in the majority of cases and are not subject to extremities by one particular police officer or in one particular week or zip code since we examined each officer, zip code, and week individually.

One of the most striking results is for White officers, across the four different zip code race profiles, they were less likely to give tickets in predominantly White zip codes (6.47% less likely than Asian officers in Asian/other zip codes) than in any minority zip codes, with Hispanic (2.21% more likely) and Black (2.59% less likely) zip codes receiving the most and second most tickets in comparison, respectively. Despite our results being in comparison to Asian officers in Asian/other zip codes, by comparing only how White officers ticket, we see clear evidence of skewed ticketing behavior by zip code racial demographics.

A similar analysis among Black and Hispanic officers yields more murky results. For instance, for Black officers, only ticketing behavior in predominantly Black zip codes produced

significant results, so we could not see clear evidence for varying ticketing behavior across zip code racial characteristics. What was interesting, however, was that Black officers demonstrated a propensity to ticket more in Black zip codes (2.74% more likely) than their White counterparts in any zip code. For Hispanic officers, insignificant results again prevented us from analyzing behavior in Black and Hispanic zip codes, but we were able to note that these officers give the least amount of tickets in predominantly White zip codes (7.53% less likely). They also gave the second lowest number of tickets in Asian/other zip codes (6.02% less likely), similar to White officers in the same areas.

Looking to other zip code characteristics, crime rate also impacts ticketing behavior, with a higher crime rate correlating with an increase in the number of tickets given by White and Hispanic officers (the effect on Black officers was not statistically significant). Even here, though, it seems like White officers are more impacted by crime rate than Hispanic officers (1.24 times more likely), with these officers seeing the greatest increase in tickets given in zip codes with higher crime rates. An increase in the median income of a zip code also correlated with increased ticketing behavior across all races, a finding that we found surprising since we expected the opposite to be true. A potential explanation for this might be the influx of tourists and businesses in these areas that lend themselves towards more potential instances of parking violations, but this is simply a theory.

What is important to take away from these results, however, is that while there does seem to exist bias in ticketing behavior among White police officers, we cannot point to a clear trend of discrimination for all police officers. Crime rate is also a good predictor of ticketing, and white areas receive fewer tickets than most other minority areas, but we cannot draw overarching conclusions for discriminatory behavior.

VII. Discussion

With these results, it is important to keep in mind a few key considerations. First, our results are consistent for the majority of officers, but this does not mean that outlier officers do not exist. There will still be racist officers in any police force and officers that give a disproportionate amount of tickets compared to their peers; our analysis does not hold true for them. Second, we chose to analyze police discrimination through the lens of parking tickets since we believed it served as a good proxy to examine implicit bias and ingrained heuristics on the part of police officers. While we cannot make overarching conclusions about racism within police forces as it relates to parking tickets, this does not exonerate racist actions in other aspects of their job.

Despite the strength of our dataset in both its size and completeness, our research had limitations. First and foremost, we used a proxy to infer the race of police officers rather than their actual races. Not all minority officers have non-White names (Fryer & Levitt, 2004), so determining the actual race of these individuals is key in determining the accuracy of our results. In addition, we did not account for all potential factors that could affect parking ticket disbursement. For instance, although we ensured variation in zip codes patrolled over the course of an officer's career, we could not control for how beats were assigned and whether certain officers were more likely to be assigned to certain areas. Future studies should replicate this approach in other cities and use officers' actual races instead of a proxy.

This study came about from an interest in prior literature on racist police policies like stop-and-frisk; police discrimination still exists and disproportionately affects minority communities. Our findings only apply to parking ticket enforcement. This brings up an important distinction between systematic racism and systemic or structural racism. Despite the fact that we

could not draw definitive results on implicit bias in police discrimination through parking tickets, the fact remains that zip codes with predominantly minority communities see higher rates of parking tickets. The original ProPublica study from which we received our data found this, and this sort of discrimination is likely a result of poor infrastructure within the city and lack of investment in these parts of Chicago. Decades of housing discrimination policies have created segregated neighborhoods that do not receive the same sort of infrastructure investment as whiter areas, so poorly maintained roads and lack of signage, among other issues, create an environment where receiving a parking ticket is a lot easier. Combine this inequity of resources with discriminatory policing behavior beyond parking ticket issuance and minority communities become victims of an unfair system, incurring financial debt that they often can't afford and struggle to escape.

With regards to policy implications, more research must be conducted to find stronger results that could suggest clearer policy ideas and then analyze the impact of those policy ideas and their efficacy. Chicago can, in the short term, invest in improved bias training for all police officers, emphasizing implicit forms of bias that have more subtle effects on police perception. This sort of training only goes so far but making officers more aware of their natural biases is the first step in reducing these disparities and creating more impactful policies.

VIII. Conclusion

Through this research, we sought to study whether implicit bias plays a role in parking ticket disbursement in Chicago. While we were unable to find trends in how all police officers issue parking tickets when accounting for zip code characteristics, we did conclude that White officers exhibit racial bias based on the zip code demographics of where they ticket, favoring

White communities to Black and Hispanic ones. Further research should be done to validate these results without the use of a race proxy and in other cities, but immediate implementation of more nuanced bias training should be a short-term goal to mitigate these disparities.

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Appendix

Appendix A: Map of racial segregation in Chicago (Silver, 2015)
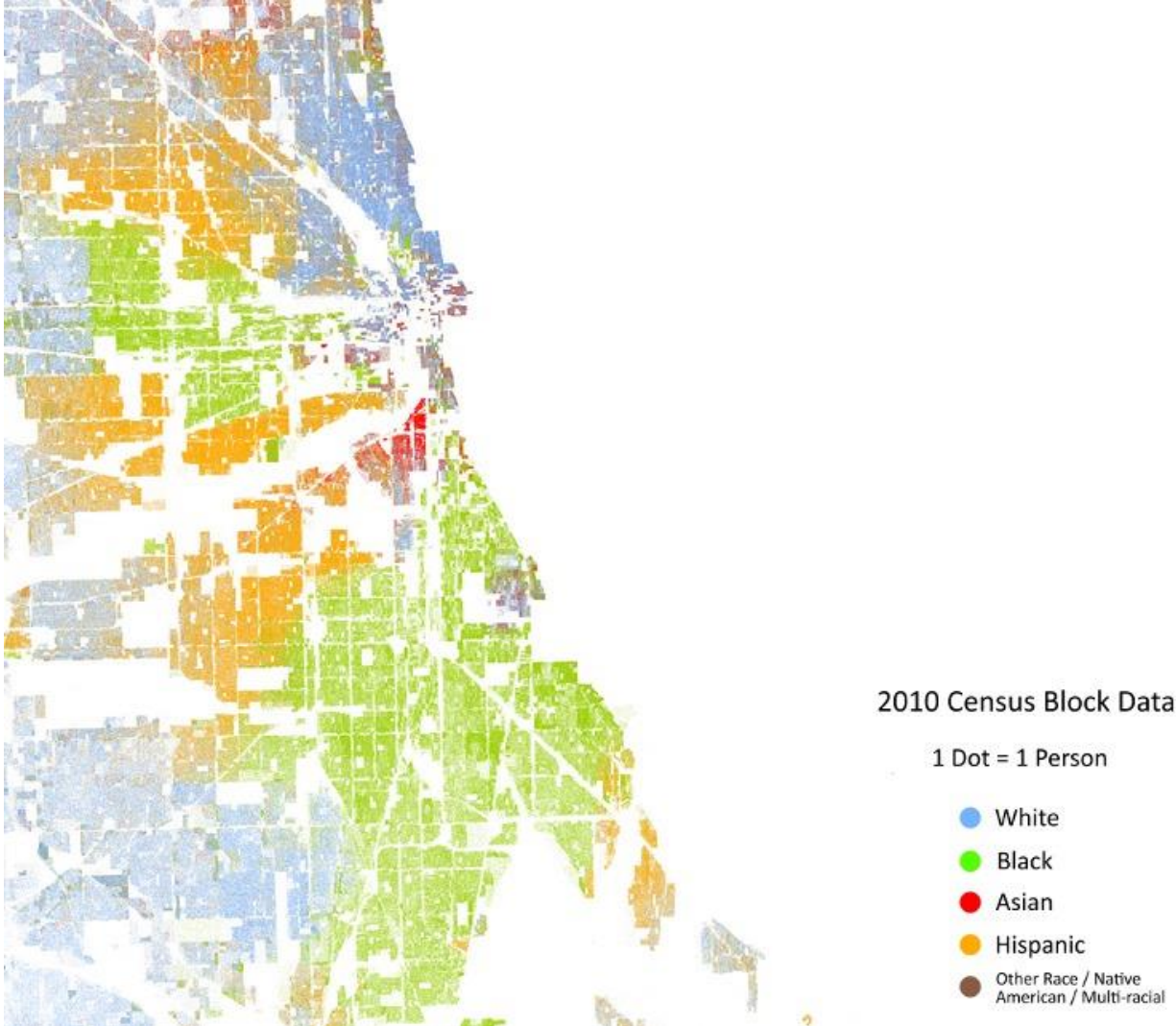
Appendix B: Sample of original ProPublica parking ticket data

ticket_number	issue_date	violation_location	license_plate_number	license_plate_state	license_plate_type	zipcode	violation_code	violation_
51551278	2007-01-01 00:00:00	6014 W 64TH ST	90ad622c3274c9bdc9d8c812b79a01d0aaf7479f2bd7431f...	IL	PAS	60638	0976160F	EXPIRED P
51491256	2007-01-01 00:00:00	530 N MICHIGAN	bce4dc26b2c96965380cb2b838cdbb95632b7b571606125...	IL	PAS	606343801	0964150B	PARKING/
50433524	2007-01-01 00:01:00	4001 N LONG	44641e828f4d894c883c07c566063c2d99d08f2c03b3d4168...	IL	PAS	60148	0976160F	EXPIRED P
51430906	2007-01-01 00:01:00	303 E WACKER	eee50ca0d9be2debd0e7d45bad05b8674a6cf5b892230f5...	IL	PAS	60601	0964110A	DOUBLE P
51507779	2007-01-01 00:01:00	7 E 41ST ST	244116ca3eed4235b1f61f6d753d8c688be2a48c9fdd976fa...	IL	PAS	605053013	0976220B	SMOKED/
51260468	2007-01-01 00:03:00	1039 W LELAND	b167d28412271c62a8e30cbb5396ffb97f12c08382f9a6f46...	IL	TMP	60632	0964150B	PARKING/
51501733	2007-01-01 00:04:00	2405 W 14TH ST	b27d76408581e0e3940aa2722fa87bd23cd5428be4c46c7c...	IL	PAS	60651	0964110A	DOUBLE P
51260469	2007-01-01 00:05:00	1039 W LELAND	59cc36a038a7290643aea2e7a48001f9fef5f0b8518ede7ae...	IL	PAS	60643	0964150B	PARKING/
51417189	2007-01-01 00:05:00	6900 N GREENVIEW	cf5b8e9e5b9ec85ce46bee319e9c1d45ae6f6feb8b29939c2...	IL	TMP	60651	0964125	NO CITY S
51579563	2007-01-01 00:05:00	6900 N GREENVIEW	cf5b8e9e5b9ec85ce46bee319e9c1d45ae6f6feb8b29939c2...	IL	TMP	60651	0964150B	PARKING/
51507781	2007-01-01 00:05:00	9 E 41ST ST	81f2b5e908e108b3e1524676d7a736f22e56c0b2b4128db1...	IL	PAS	606532213	0976220B	SMOKED/
51221093	2007-01-01 00:05:00	4956 N OAKLEY	d5bd4564db89cb1fdb1cc4465c554dbe6910fb5513aa195...	IL	PAS	601481629	0976160F	EXPIRED P
51221094	2007-01-01 00:05:00	4944 N OAKLEY	f3ec75e4c24eb68836cd463d8e1a487e78dd72a54a80235a...	IL	PAS		0976160F	EXPIRED P
51507780	2007-01-01 00:05:00	9 E 41ST ST	81f2b5e908e108b3e1524676d7a736f22e56c0b2b4128db1...	IL	PAS	606532213	0976160A	REAR AND

Appendix C: Sample of police officers in Chicago with badge numbers

	ALL SWORN		11/7/2016
NAME		STAR NO	
AARON, JEFFERY		1424	SERGEANT
AARON, KARINA		13705	POLICE OFFICER
ABBATE, TERRY		19596	POLICE OFFICER
ABDALLAH, ZAID		17673	POLICE OFFICER
ABDELHADI, ABDALMAHD		7147	POLICE OFFICER
ABDELMAJEID, AZIZ		14008	POLICE OFFICER
ABEJERO, JASON		14237	POLICE OFFICER
ABNEY, PATRICK		11360	POLICE OFFICER
ABRAHAM, NANCY		16579	POLICE OFFICER
ABRAM, ANTHONY			POLICE OFFICER

Appendix D: Sample of proxy for assigning race to first names

firstname	obs	pcthispanic	pctwhite	pctblack	pctapi	pctaian	pct2prace
AARON	3646	2.880	91.607	3.264	2.057	0.055	0.137
ABBAS	59	0.000	71.186	3.390	25.424	0.000	0.000
ABBEY	57	0.000	96.491	3.509	0.000	0.000	0.000
ABBIE	74	1.351	95.946	2.703	0.000	0.000	0.000
ABBY	262	1.527	94.656	1.527	2.290	0.000	0.000
ABDUL	221	0.452	44.344	6.787	47.511	0.452	0.452
ABDULLAH	44	2.273	65.909	9.091	22.727	0.000	0.000
ABE	31	6.452	77.419	12.903	3.226	0.000	0.000
ABEL	327	82.569	12.844	2.141	2.446	0.000	0.000
ABELARDO	76	78.947	9.211	0.000	11.842	0.000	0.000

Appendix E: Regression output for diff-in-diff model with fixed effects

```
> model6 <- felm(tickets~white:(white_zip_avg + black_zip_avg + hispanic_zip_avg + Asian_other_zip_avg
+ median_income_avg + crime_rate_avg) + black:(white_zip_avg + black_zip_avg + hispanic_zip_avg + Asian
_other_zip_avg + median_income_avg + crime_rate_avg) + hispanic:(white_zip_avg + black_zip_avg + hispan
ic_zip_avg + Asian_other_zip_avg + median_income_avg + crime_rate_avg)| wk_cont + officer + zipcode, da
ta=df_all)

Coefficients:
                                Estimate Std. Error t value Pr(>|t|)
white:white_zip_avg            -6.474e-02  1.427e-02  -4.538 5.67e-06 ***
white:black_zip_avg            -2.587e-02  1.124e-02  -2.302 0.021335 *
white:hispanic_zip_avg          2.208e-02  9.955e-03   2.218 0.026551 *
white:Asian_other_zip_avg      -4.500e-02  2.051e-02  -2.194 0.028258 *
white:median_income_avg         4.997e-07  1.152e-07   4.337 1.44e-05 ***
white:crime_rate_avg            5.450e-06  1.455e-06   3.747 0.000179 ***
white_zip_avg:black            -1.877e-02  1.800e-02  -1.043 0.297003
black_zip_avg:black             2.735e-02  1.458e-02   1.876 0.060627 .
hispanic_zip_avg:black         -1.417e-02  1.315e-02  -1.078 0.281188
Asian_other_zip_avg:black      -3.337e-02  2.550e-02  -1.309 0.190699
median_income_avg:black         7.779e-07  1.379e-07   5.639 1.71e-08 ***
crime_rate_avg:black            2.018e-06  1.675e-06   1.205 0.228157
white_zip_avg:hispanic         -7.526e-02  1.450e-02  -5.190 2.10e-07 ***
black_zip_avg:hispanic         -1.826e-02  1.141e-02  -1.600 0.109611
hispanic_zip_avg:hispanic       9.569e-03  1.011e-02   0.947 0.343860
Asian_other_zip_avg:hispanic   -6.017e-02  2.090e-02  -2.878 0.003997 **
median_income_avg:hispanic      9.649e-07  1.176e-07   8.205 2.30e-16 ***
crime_rate_avg:hispanic         4.407e-06  1.475e-06   2.987 0.002813 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5488 on 40948741 degrees of freedom
Multiple R-squared(full model): 0.0504    Adjusted R-squared: 0.05017
Multiple R-squared(proj model): 4.029e-05    Adjusted R-squared: -0.0002039
F-statistic(full model):217.4 on 9998 and 40948741 DF, p-value: < 2.2e-16
F-statistic(proj model): 91.67 on 18 and 40948741 DF, p-value: < 2.2e-16
*** Standard errors may be too high due to more than 2 groups and exactDOF=FALSE
```