# Agency Incentives and Disparate Revenue Collection: Evidence from Chicago Parking Tickets*


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**Abstract**

We leverage a sharp 2012 parking fine increase for failing to purchase vehicle registration to examine disparate ticketing patterns across enforcement agencies in Chicago. Using an event-study framework, we find that Chicago police increased their enforcement of car registration non-compliance in Black relative to non-Black neighborhoods, with no observed disparate response for non-police enforcement agencies. This disparity is unexplained by differences in non-compliance and is instead driven by departmental revenue incentives and lower marginal search costs in Black neighborhoods. Disparate enforcement also exacerbated existing gaps in financial instability, including increased rates of ticket non-payment and bankruptcy filings in Black neighborhoods.



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# 1 Introduction

Parking fines are major revenue generators for cities in the United States. Chicago raised $264 million from parking citations in 2016, equivalent to an annual $97.20 per-capita tax; similarly, New York City raised $565 million from parking fines in 2015 (Diskin, 2019; Digital Editors, 2021). The ability of a city to raise revenue from these types of fines depends on its enforcement and collection policies and its residents' ability to pay these fines. Reliance on local revenue from these fines and fees can have significant economic consequences on residents, especially those with lower ability to pay (Makowsky and Stratmann, 2009, 2011; U.S. Department of Justice Civil Rights Division, 2015).[1]

Local governments rely on agents to enforce parking violations, including police officers, parking enforcement aides, and other third-party contractors. Thus, the equity and efficiency of parking enforcement across neighborhoods are dependent on the agents whom the local government hires. Consequently, agents may disparately enforce violations across areas if they are maximizing a different objective function than the government - for example, minimizing search costs or focusing on alternative, non-parking enforcement responsibilities.[2] To the extent such wedges between government and agent exist and are correlated with racial and ethnic divisions within a metropolitan area, agents may respond to collection incentives in ways that generate disparate outcomes in the population while also harming revenue.

In this paper, we examine whether an increase in motor vehicle registration, which we refer to as "stickers," and the related fine for non-compliance affected parking enforcement patterns in Chicago. This 2012 policy increased the cost of vehicle registration from $120–$135, an 11% increase, and the fine for registration non-compliance from $120–$200, a 67% increase. Thus, it simultaneously made compliance more expensive and enforcement more profitable relative to other parking fines. Aggressive enforcement and punishment had severe consequences on Chicago residents, particularly in predominantly Black neighborhoods. While Black neighborhoods accounted for only 22% of tickets, they accounted for 40% of all debt, with the average debt doubling from $1,500 in 2007 to $3,900 by 2017 (Sanchez and Ramos, 2018).

Since both Chicago Police Department (CPD) and other agents, primarily but not exclusively parking enforcement agents (PEA or non-CPD), can enforce municipal parking laws, we separately examine the impact of the sticker tax increase on both types of agents, with

[1] Propublica estimates that unpaid parking debt alone in Chicago totals over $1.6 billion debt, with an average debt of $3,900 per ticket (Samuelson, 2018).

[2] There is a long literature examining multi-task principal-agent models and empirically investigating agent responses in the face of differing incentives. For example, see Holmstrom and Milgrom (1991) and Aghion and Tirole (1997) for the canonical theory, and Jacob and Levitt (2003) and Knutsson and Tyrefors (2022) for empirical work in the context of teachers and ambulances, respectively.

the major distinction being that while PEAs are evaluated on their ticketing productivity, CPD officers are not.[3] Furthermore, CPD officers have additional responsibilities to "work for the benefit of its citizens by protecting life and property from harm and maintain order" (Department of Human Resources, 2023). Thus, the budget reform provides a unique opportunity to evaluate how governments use different incentives across various agents to affect revenue-generating enforcement and the downstream impact this has across residents.

To test for disparate enforcement across the two types of agents, we use administrative parking ticket data from 2007 to 2016 in Chicago and a difference-in-differences (DiD) framework to estimate the relative change in sticker enforcement across various types of neighborhoods, focusing on Black versus non-Black areas due to the purported claims of disparate impacts from the general public.[4] Across Black versus non-Black neighborhoods, our results show consistent evidence of a disparate response for CPD-issued tickets. We find that CPD sticker enforcement increased by nearly 2,500 tickets in Black relative to non-Black neighborhoods per year. We also find that non-sticker ticket enforcement significantly increased by nearly 12,000 tickets, despite the non-sticker fines remaining largely the same. We interpret these patterns as evidence of a broader revenue collection effort. Our results also show evidence of differential substitution between ticket types between Black and non-Black neighborhoods with CPD sticker enforcement in Black neighborhoods increasing by 3.8 percentage points (p.p.) more than non-Black neighborhoods.

Given that both the cost of registration and the fine increased simultaneously, this disparate impact could reflect differential enforcement or compliance across Black and non-Black neighborhoods.[5] Using sticker purchasing data at the neighborhood level from 2007–2016, we rule out the latter. Through a decomposition exercise, we document outsized differential enforcement in Black neighborhoods, even after accounting for differences in the number of unregistered vehicles by neighborhood. Coupled with similar purchasing responses, these results further underscore that the patterns we document are predominantly due to CPD enforcement rather than simply reflecting differences in baseline compliance.

CPD's increased enforcement in Black neighborhoods relative to non-Black neighborhoods had downstream implications on the source of collected revenue and financial outcomes (e.g., bankruptcy) of those ticketed. At the ticket level, we find that revenue per ticket decreased by $27 in Black neighborhoods relative to non-Black neighborhoods, indi-

[3] We refer to parking enforcement agents as PEA or non-CPD interchangeably.

[4] We also stratify across income and ability to pay and do not find similar patterns of disparate enforcement for CPD and non-CPD issued parking tickets.

[5] Variation in neighborhood characteristics (e.g., number of parking meters) and its residents (e.g., number of vehicle owners with valid registration) may also lead to differential non-compliance which could warrant differential enforcement, holding fixed policing patterns.

cating increased instances of nonpayment and financial strain.[6] Accordingly, we estimate an 8.2 p.p. decrease in the likelihood of payment and a 1.5 p.p. increase in the likelihood of declaring bankruptcy per ticket issued in Black neighborhoods, relative to non-Black neighborhoods, with both effects significant at the 99% level. The increased sticker enforcement neighborhood level by CPD also shifted the tax burden from non-Black neighborhoods to Black neighborhoods. Collected revenue increases by over $270,000 more in Black neighborhoods relative to non-Black neighborhoods, which represents an increase of $5 per capita.[7] In sharp contrast, non-CPD agents collect greater revenue from non-Black neighborhoods.

Given the starkly different CPD and non-CPD responses to the sticker fine, we conduct a series of exercises to better understand the mechanisms behind the differential responses. Using alternative non-race neighborhood characteristics, we show that CPD officers increased their sticker ticket enforcement in neighborhoods with high pre-reform sticker ticket concentrations and higher crime rates, while non-CPD officers are relatively unresponsive along these margins. Moreover, we show that between 2011 and 2012, CPD enforcement increased nearly 50% on the first day the sticker fine was enforceable, almost three times the corresponding non-CPD enforcement change. Linking these results to institutional details on the responsibilities and evaluation criteria of agents across each department, we argue that non-CPD behavior was not differentially responsive to the policy due to its incentive for maximizing ticket volume rather than collected revenue or concentrating on ticket type. In contrast, CPD officers issue tickets as one of many distinct responsibilities, suggesting that encouraging CPD sticker tickets may be inefficient both in an equity and revenue collection sense.

When examining the joint distributions of neighborhood-level tickets and sticker purchases, we find that non-CPD enforcement behavior is virtually uncorrelated with changes in sticker purchases across neighborhood types, while CPD responses exhibit sharply distinct patterns, both in slopes and levels. When correlating changes in enforcement with pre-reform neighborhood characteristics, we consistently find greater levels of CPD enforcement in Black neighborhoods, even across neighborhoods that share similar rates of ticket-to-purchase ratios or ticket payment rates. We present evidence that the observed differential enforcement is due to incentive-induced increases in officer ticketing efforts and lower marginal search costs in Black neighborhoods. Evidence of lower search costs includes the geography of crime (and, by assumption, policing) in Chicago and the fact that sticker tickets in non-Black neighborhoods are nearly twice as likely to be issued in parking structures.

[6] While we also find broadly similar estimates for tickets issued by PEAs, these results are partly a function of noisier pre-trends, and so we interpret them with caution.

[7] The average population in a Black neighborhood in our sample during the relevant period is approximately 51,000.

Finally, we estimate officer-specific responses to the budgetary reform and show that 65-85% of officers increase their sticker ticketing volume after the fine increase. Across the officer distribution, the marginal sticker ticket is also almost twice as likely to be written in a Black neighborhood than in a non-Black neighborhood. Regressing officer characteristics against our estimated policy responses reveals few strong correlations, but the empirical patterns we observe can also not be fully explained by the neighborhood demographics of officer assignments. Instead, we conclude that the disparate enforcement across neighborhoods was part of a broader departmental phenomenon and revenue collection effort in response to the budget reform and existing deficit.

This paper builds empirical evidence on incentives and the behavior of public sector agents and their role in revenue generation for local governments.[8] We build on prior work studying the responses of police officers to pay (Mas, 2006) and opportunities for overtime compensation (Chalfin and Goncalves, 2021). We show that police officers in our setting are responsive to governmental revenue goals in ways that are not present among contracted agents, likely due to differences in incentives across agencies, and that this response leads to disparate revenue collection and financial outcomes in the population.[9]

Our work also connects to a rich literature in public finance studying how the structure of tax enforcement and laws may contribute to disparities and evasion (Allingham and Sandmo, 1972). For instance, work has shown that Black homeowners pay higher property taxes (Avenancio-León and Howard, 2022), Black taxpayers are more likely to be audited for claiming the earned income tax credit (Elzayn et al., 2023), and Black married couples are more likely to incur a "marriage penalty" in income taxes (Brown, 2022; Holtzblatt et al., 2023). We show an additional channel through which revenue-generating policies have disparate impacts: city car registration.

Our results also contribute to the growing body of literature studying disparate policing in the United States.[10] Notably, our findings align with Goncalves and Mello (2021), who also find racial disparities in officer discretion when issuing speeding fines. In our context, an officer's ticketing choice is less likely to be confounded with concerns for public safety than in other contexts. For example, failing to stop a speeding driver in the case of highway ticketing choice could have more severe consequences than failing to ticket an improperly parked car. Furthermore, given our rich data, we can cleanly measure the monetary and

[8]For theoretical work in this area, see Prendergast (2007, 2008) and for a review on incentives and decision making, see Kamenica (2012).

[9]Prior work in public finance shows tax collectors are responsive to performance pay (Kahn, Silva, and Ziliak 2001; Khan, Khwaja, and Olken 2016). For more on the role of law enforcement in revenue collection, see Harvey (2020), Goldstein, Sances, and You (2020), and Makowsky, Stratmann, and Tabarrok (2019).

[10]See Owens and Ba (2021) for a comprehensive literature review on policing and disproportionate burden across demographic subgroups.

revenue implications of disparate policing.

Recent work on financial sanctions in the justice system has found mixed evidence of the impact of these sanctions on outcomes. Recent work by Pager et al. (2022) and Finlay et al. (Forthcoming) shows that financial sanctions from a criminal conviction have no long-term or short-term impact on labor market or recidivism outcomes. However, Goncalves and Mello (2023), Mello (2023), Kessler (2020), and Hansen (2015) have found negative impacts on financial outcomes but reduced recidivism from harsher fines.

## 2 Institutional Background and Setting

Chicago is often recognized as one of the most spatially segregated cities in the United States, accompanying wide racial gaps in socioeconomic outcomes. For example, Black-owned businesses are valued at less than one-twelfth the value of white businesses, and the median household income for Black families ($30,303) is less than half that of white families ($70,960) (ProsperityNow, 2017). These inequalities also extend to local crime rates and rates of contact with the criminal justice system. Black neighborhoods experience substantially higher homicide rates (Sharkey and Marsteller, 2022), and Black motorists comprise the majority (60%) of traffic stops in the city (Goudie et al., 2024). Importantly for this paper, this increased exposure to law enforcement also creates more sticker ticket enforcement, as officers are more likely to observe any expired registrations given the higher rates of contact in Black neighborhoods. These features imply that any changes to CPD sticker enforcement patterns will also have a disproportionate impact in Black neighborhoods.

The city of Chicago relies heavily on parking ticket revenue, with 7% of its 3.6 billion dollar operating budget coming from the fines it collects. Each year, the city issues over 3 million tickets for parking violations, vehicle compliance, and automated traffic camera violations (Sanchez and Kambhampati, 2018).

Chicago's parking fine is particularly punitive. Unpaid fines double 25 days from the initial ticket issue date. After three unpaid parking tickets, red light tickets, or speed camera tickets within a year or two unpaid parking tickets, red light camera tickets, or speed enforcement tickets that are one year past due, the car can be impounded or booted, and the vehicle owner receives a seizure notice. After ten or more non-moving violations or five unpaid tickets from automated red-light or speed cameras, the city of Chicago suspends the vehicle owner's driver's license. Drivers can choose to enter into a payment plan with the city, but to qualify for the standard payment plan, the driver must pay a $1,000 down payment on total vehicle debt plus payment in full on any tow, boot, or storage fees. If the driver is unable to commit to a plan, the driver can then declare bankruptcy. Chicago also has anti-scofflaw rules that prevent those with unpaid tickets or debts to the city from accessing contracts, licenses, or grants. For example, municipal jobs, such as driving a taxi or teaching in a classroom, are inaccessible for those with unpaid parking tickets. Parking debt in Chicago can follow the driver for an entire lifetime.[11]

Column 1 of Table 1 shows the top ten parking tickets by total revenue collected from 2007 to 2011. The most issued ticket has a fine of $60. Of the top tickets, only three are related to parking(residential permit parking, expired meter, parking in prohibited areas). Four of the most popular tickets relate to having correct licensing or registration.

The most punitive of the parking fines is for failing to properly display the city sticker on the car windshield. The city sticker, which is colloquially known as the 'sticker tax,' is an annual registration fee that Chicago residents with vehicles must pay to own a vehicle in the city. While the registration is $75 for sedans and $120 for larger passenger vehicles, the fine for failing to buy the sticker or failing to display the sticker is almost double that of the next expensive ticket, at $120 plus a $40 late fee. In October 2011, Mayor Rahm Emmanuel announced the city would be raising the registration fee for the stickers from $75 to $85 for smaller passenger vehicles and $120 to $135 for larger passenger vehicles (Civic Federation, 2012).[12] Further, the fine for not paying the tax would increase by two-thirds, from $120 to $200. The increases were announced in October 2011 and fine increases began in February 2012.

The fee increase was announced in conjunction with other aggressive revenue-generating policies in an attempt to close a $637 million projected deficit in the 2012 budget (Emanuel, 2011). One of these policies was an aggressive debt collection plan that directly affected how the city collected and enforced payment of parking ticket fees. This plan would allow the city to begin garnishing the wages and tax returns for high debtors. Once the maximum amount of fees had been levied, the city could garnish drivers' state tax returns and 15% of wages (Andriesen, 2012). The stated goal of this aggressive debt collection plan for parking and traffic infractions was to reduce employee indebtedness and to hold rental car companies accountable for their parking fines. For city employees, the mayor announced additional punishments. For example, City Hall workers could face suspension or be fired for owing anywhere between $250 to $1000 and more (Ruthhart and Reporter, 2014).

Both the Chicago police and parking enforcement agents (which include both PEA and other non-CPD agencies) can issue parking citations. PEAs can enforce non-moving ordinances in Chicago and are either employed directly by the city (e.g., the Department of

[11]This, and the degree of Chicago's reliance on parking fine revenue are unique. Los Angeles and New York City have statutes of limitation that are 5 and 8 years, respectively.

[12]Vehicles with a curb weight less than 4,500 pounds are defined as small passenger vehicles. Vehicles between 4,501 to 16,000 pounds are large passenger vehicles.

Revenue) or through a third-party firm (e.g., SERCO). PEAs believe they are evaluated based on their ticketing productivity and are sometimes promoted based on their tickets per shift.[13] In contrast, Chicago police officers' main job function is not parking enforcement, and their parking ticket productivity is not as important to their careers. Furthermore, Chicago policymakers have been shifting toward banning traffic ticket quotas for police officers in recent years. In 2019, Illinois passed a law explicitly forbidding law enforcement agencies from evaluating personnel based on their ticket-issuing productivity; Chicago scaled back many of the harsher sticker ticket penalties. This was partly due to the criticism towards CPD for mandating a minimum number of traffic stops prior to the passage of the law (Main, 2017). To the best of our knowledge, CPD officers were not required to fulfill any quotas for parking tickets and any reference to ticket quotas was in relation to traffic infractions. A simple rationalizing model that formalizes differences between CPD and non-CPD objectives is in Appendix B.

## 3 Data

ProPublica Illinois, in partnership with WBEZ Chicago, obtained and publicly released parking ticket data from the city of Chicago from 2007 to 2018. The data include information on the date and time of the ticket, where the vehicle was parked, the badge number of the ticketing officer, de-identified license plates, make, registration zip code, citation reason, and, importantly, payment status. This payment status includes information on the ticket outcome, such as whether the vehicle owner received a notice of seizure, whether the vehicle owner received a notice of driver's license suspension, and whether the vehicle owner declared bankruptcy as a result of the ticket. It also includes information on how much of the fine remains unpaid, the date of the last payment, and the initial fine amount.

Given geographic patterns of policing and PEA assignment, a key object of analysis for this paper is the area the ticket was given. We consider two levels of aggregation: zip code and Census tract. The raw ticketing data does not include zip code or tract of violation location. To recover this information, we use the Census Geocoder. This successfully codes a vast majority of the tickets in our sample. The remainder are coded using geocoder.us. Where zip codes are unavailable from these matches, we use their latitude and longitudes to map into the relevant zip based on Census GIS shapefiles. To determine if a zip code neighborhood is considered Black or non-Black, we match each zip code to the Census 5-digit Zip Code Tabulation Area (ZCTA5) using the American Community Survey (ACS) 5-Year estimates for 2007 - 2011. The ZCTA5 are approximate area representations of zip codes in

[13]This is based on reading work testimonials from Indeed.com.

the United States but are not exact matches for zip codes since ZCTA5s are aggregated from Census blocks. Despite this, they are close matches for each other. Tract demographics can be measured directly. We show in Section 5.1 that our results are robust to our choice of geographic aggregation.

We obtained sticker registration (purchase) data by zip code using a Freedom of Information Act filed with the City Clerk of the city of Chicago. While ideally, we would be able to measure compliance at the vehicle or individual level of observation, to protect the purchasers' privacy, this information only contained the zip code of the buyer's billing address. The data contains information on the date and time of the purchase, the full purchase amount, and the type of vehicle the sticker was for. We map each sticker purchase to a ZCTA5 using the zip code. Because this analysis can only be conducted at the geographic level of zip, we present the ticketing results at the zip code level as well (and show the—very similar—tract levels results in the appendix).

We present summary statistics describing the ticketing data in Table 1.[14] This table reports average annual characteristics of the top ten revenue-generating tickets from 2007-2011 and characteristics for the same set of tickets from 2012-2016.[15] The type of ticket is listed in each row. We show annual ticket volume, annual ticket revenue, modal fine amount, the revenue share of the listed ticket along with the revenue share rank in Columns 5 and 11, and the ratio of revenue received to expected revenue, where expected revenue is calculated as the base fine amount times ticket volume. The revenue share is less than one when collected revenue plus applicable late fees is less than the expected collected amount if all written tickets were paid on time and is greater than one if the collected revenue plus applicable late fees exceeds this expectation.

Our analysis focuses on comparisons between Black (defined as $\geq 75\%$ Black) neighborhoods compared to non-Black neighborhoods across several ticket-related outcomes, including the type of ticket based on the violation code (sticker ticket or another type of ticket). We also include several point-in-time measures (these measures evolve over time but are current as of the latest data extract in 2019): the amount of revenue collected from the ticket, if a ticket was dismissed (either internally or as a result of an appeal) fully paid, given a notice of non-payment (if the ticket was not yet paid and the city sent a notice to the address on file for that vehicle), or included as a debt in a consumer bankruptcy case.

We show descriptive statistics summarizing the most salient data features in Table 2

[14] Displayed separately by neighborhood demographic group in Appendix Table A1.

[15] We limit the data to 2016 to ensure our estimates are uncontaminated by a series of Chicago Police Department Reforms (e.g., `https://www.chicago.gov/content/dam/city/depts/mayor/Public%20Safety%20Reforms/ProgressReport-PoliceReforms.pdf`) enacted after 2016. Our results throughout are highly similar if we use data through 2018 instead.

for the five years before the sticker policy change (2007-2011). Panel A of this table shows information at the ticket level. About 60% of tickets in Black neighborhoods are written by CPD, who also write fewer than half of tickets in non-Black areas. About 15% of tickets written in Black areas are sticker tickets, while this rate is close to 6% in non-Black areas. Outcomes after receiving a sticker ticket are worse for people who receive tickets in Black areas as they are less likely to fully pay the ticket or have the ticket dismissed and more likely to be involved in bankruptcy or have a non-payment notice.

Panels B and C show these same outcomes at the neighborhood level. Black areas have slightly larger populations on average (about 51 thousand compared to about 47 thousand in non-Black areas) but also have fewer vehicles (about 17 thousand compared to 21 thousand). Black neighborhoods have fewer stickers purchased (16 thousand compared to 21 thousand) and slightly lower ratios of stickers purchased relative to the number of total vehicles (95% compared to 100%).[16] The number of total tickets written by the CPD is lower in Black neighborhoods, although more of them are sticker tickets. Substantially more sticker tickets are written in Black neighborhoods (2000 more per year).

We present the raw geographic dispersion of several key measures in Appendix Figure A1. This figure shows which zip codes are greater than 75% Black (no zip code crosses the threshold to change classifications during our sample period). It also shows the dispersion of crime (from the CPD open data portal), sticker tickets issued by CPD and non-CPD agents, and parking lots and garages in the city of Chicago (which we code based on data from Open Street Maps). The similarities between the geographies of crime and CPD-issued sticker tickets provide early evidence of the multi-tasking and effort channels discussed throughout this paper.

To understand underlying mechanisms and heterogeneous responses, we need information on officers. Our ticketing data includes officer badge numbers. Because these identifiers can change, we build an officer badge crosswalk using data from OpenOversight. We combine this with data from the Invisible Institute to generate an officer-level data set with information on the number and type of tickets written, unit and employment history, complaints against the officer, and officer demographic information (race/ethnicity, sex, and age).

## 4 Empirical Strategy

Our objective is to estimate the relative effects of the ticketing reform on parking enforcement patterns across neighborhoods. We summarize this difference-in-differences approach in two

[16]Our measure of neighborhood-level vehicles is survey-based and constructed from the aggregation of several categories of survey responses, one of which is topcoded. Therefore, a strict interpretation of the number of vehicles should be made with caution.

equations. First, in Equation (1), we present event study evidence comparing majority ($\geq 75\%$) Black ($Black_i$) areas to non-majority Black areas, focusing on the $\alpha_t$ coefficients traces the evolution of an outcome of interest relative to 2011, the year prior to the sticker policy change. This allows us to carefully evaluate parallel trends.

Another identifying assumption for a difference-in-differences analysis is no impact of the treatment on the control group. In our setting, changing the sticker policy likely also impacts outcomes in non-Black areas. What we recover from our analysis is not the overall impact of the policy on our outcomes but rather the differential impact of the policy on Black areas relative to their non-Black counterparts. Formally, for neighborhood $i$ and year $t$, we estimate:

$$Y_{it} = \alpha_0 + \sum_{\substack{t=2007 \\ t\neq 2011}}^{2016} \alpha_t(Black_i \times Year_t) + \sigma_i + \lambda_t + \varepsilon_{it} \tag{1}$$

Second, we summarize our results in a single point estimate in Equation (2). Conditional on our identifying assumptions, $\beta_1$ of this equation summarizes the impact of the policy change in the follow-up period (2012-2016).

$$Y_{it} = \beta_0 + \beta_1(Black_i \times Post_t) + \sigma_i + \lambda_t + \epsilon_{it} \tag{2}$$

A two-way fixed effects strategy is appropriate in this setting as treatment occurs simultaneously for all treated units, allowing us to avoid concerns of negative weights in the presence of treatment heterogeneity (Goodman-Bacon, 2021). Additionally, we handle the potential complications of continuous treatment by defining a binary treatment indicator defined as ($\geq 75\%$) Black zip codes (Callaway, Goodman-Bacon, and Sant'Anna, 2021).

Sticker purchasing data is only available at the zip code level while ticketing data is available at both the zip and tract geographic levels. For consistency across exercises, we show the zip code results in the main text. In robustness checks below, we show that our results are similar when we instead define neighborhoods at the tract level. Moreover, while discretizing the treatment allows us to avoid the challenges of continuous treatment in DiD settings, the choice of treatment cutoff may be important for interpreting our results. Section 5.1 shows that our results are robust to both higher and lower thresholds.

# 5 Results

We begin our analysis by examining ticketing trends in the raw data. Panel A of Figure 1 plots the yearly number of CPD-issued sticker tickets issued in Black and non-Black neighborhoods (blue and grey respectively), both in level and per-capita terms (solid and dashed lines respectively). In Panel B, we also plot the same series for non-CPD agencies. In Panel A, prior to the 2012 reform, both sticker ticket series were trending downwards, with lower ticket volumes year-over-year. After 2012, however, ticket volumes in Black neighborhoods exhibited a precipitous jump upward, exceeding their pre-policy levels, while ticket volumes in non-Black neighborhoods largely flattened. In contrast, the series in Panel B are relatively flat, displaying little noticeable changes pre- or post-reform. Together, these raw data series depict evidence that law enforcement agencies disproportionately enforced sticker non-compliance in Black, compared to non-Black neighborhoods.

In order to causally link the disparate enforcement to the change in sticker tickets and other outcomes, we must rule out other potential confounding factors. For example, neighborhoods may differ in their baseline financial strain, resulting in differential non-compliance or increased probabilities of non-payment. Neighborhoods may also experience differential policing patterns, which increase the likelihood that any non-compliance is noted by law enforcement. The existence of time-varying differences would violate the parallel trends assumption and undermine any causal interpretation.

Figure 2 reports event-study coefficients on the interactions of neighborhood type and year indicators from Equation (1), estimated at the ticket level. We present corresponding difference-in-differences estimates in Table 3.[17] We begin in Panel A by examining the probability that any ticket issued is a sticker ticket, estimating separately for tickets issued by CPD (blue, solid line) and non-CPD agents (dashed, grey line) with 95% confidence intervals. Consistent with the aggregate patterns in the raw data from Figure 1, sticker tickets issued from CPD are more likely to be issued in Black neighborhoods post-reform, despite showing no measurable differential trends prior to the change. In sharp contrast, PEA agents show no discernible change in sticker ticketing behavior across neighborhood type.[18] One interpretation for this result is that non-CPD agencies were already optimizing their ticket-writing behavior and are thus less responsive to the revenue incentive the policy change induces, relative to CPD. We explore this potential mechanism in Section 5.2.

We next examine the characteristics and outcomes associated with the marginal ticket. Panel B shows that the marginal sticker ticket is associated with lower collected revenue of \$27 in Black neighborhoods, relative to non-Black neighborhoods, consistent with the higher fine amount decreasing repayment probabilities and increasing financial strain. This pattern is also consistent with the observed 8.2 p.p. reduction in repayment probabilities (Panel

[17]Non-sticker ticket point estimates and event studies are in Appendix Figures A2 & A3.

[18]The summary DiD estimate in Table 3 (Panel B, Column 1) shows a very small increase in sticker ticketing in Black neighborhoods, but this result is more an artifact of unstable pre-trends than an actual behavioral change.

C), a 6.2 p.p. increase in the probability of receiving a non-payment notice (Panel D), and a 1.5 p.p. increase in the probability of filing for bankruptcy (Panel E).[19] The empirical patterns at the ticket level suggest that the marginal sticker ticket generates less revenue in expectation in Black neighborhoods compared to non-Black neighborhoods due to the increased financial strain it places on liquidity-constrained households. Despite this, we also show that there is no change in ticket dismissal as the marginal sticker ticket is no more (or less) likely to be dismissed across neighborhood types (Panel F).[20]

In Figure 3, we estimate Equation (1) at the neighborhood, rather than the ticket level. Relative to our previous analysis, which largely captures the intensive margin of switching between sticker and non-sticker tickets conditional on writing a ticket, this neighborhood-level approach additionally captures the extensive margin of ticket writing behavior. Consistent with our previous results, Panel A shows a substantial increase in the number of CPD-written sticker tickets in Black neighborhoods compared to non-Black neighborhoods. A simple difference-in-differences (DiD) calculation, shown in Table 3, suggests that the reform led to nearly 2,500 additional sticker tickets in Black neighborhoods compared to non-Black neighborhoods on an annual basis, an increase in 0.24 sticker tickets per resident over the 5-year post-reform period. Again, non-CPD agencies show little measurable differential response. Moreover, the pre-reform estimates for both groups are generally stable and close to zero in magnitude. In contrast to the ticket-level results, however, Panel B illustrates substantial differential revenue collection across neighborhood demographic profiles for CPD-issued sticker tickets. There are increases in the number of tickets paid (Panel C), reflecting increases in collected revenue, but also increased non-payment notices (Panel D) and bankruptcy filings (Panel E). Interestingly, there are more ticket dismissals (Panel F), but this likely reflects ex-post dismissal and debt relief programs (e.g., Sanchez and Ramos 2015) rather than changes in contesting rates. Interpreted together with the ticket-level results, these patterns likely reflect both lower marginal payment probabilities and greater ticketing frequency by neighborhood.

It's possible some of the observed disparity is due to neighborhood differences in resident's ability to pay for the sticker itself, resulting in differential non-compliance with the policy. Consequently, individuals who are unable to initially afford the sticker will also be

[19] There are a small number of tickets which have an outcome that does not fall into one of these classifications (e.g., hearing requested). We abstract from estimating these outcomes separately for simplicity as they define less than one percent of the sample.

[20] For example, under a story where agencies write large amounts of sticker tickets in an attempt to meet performance expectations, we might see expect that some measure of these tickets will be thrown out ex-post if they are marginal quality. We do not see any consistent evidence of differential dismissals, although this interpretation is complicated by differential access to political capital and resources in contesting tickets by neighborhood.

unresponsive to the purchasing incentive induced by the sticker fine increase or be priced out because of the increase in the sticker price itself. Recall that our DiD estimates will account for the initial level disparity across neighborhood types, and thus capture only the differential change in sticker ticketing frequency across neighborhoods, before and after the reform. However, we take seriously the idea of quantifying differential compliance and its interaction with departmental incentives as a mechanism for our results and discuss this point in detail in Section 5.2.

### 5.1 Robustness Checks

Before assessing the mechanisms underlying our results, we first examine the stability of our estimates to a range of robustness checks. Appendix Tables A2 and A3 present robustness checks for our ticket-level and area-level regressions, respectively. Column 1 in each table reports the DiD estimate for each of our six main outcomes using only the raw data. Column 2 reproduces our estimate from the main text, adding zip code and year fixed effects in a standard DiD specification, although the results are little changed with these additions. In Column 3 of Appendix Table A2, we add controls for vehicle make, owner city, and an indicator for an out-of-state owner to account for differences across the population in the probability of receiving, contesting, and paying sticker tickets, although these controls do little to alter the point estimates from our primary specification.

Finally, in the last two columns of Appendix Tables A2 and A3, we use alternative cutoffs for defining zip codes as primarily Black. Changing the threshold to either 50 or 90%, rather than our baseline 75%, does not meaningfully affect our findings.[21]

We also decompose the main analysis for the subset of tickets that have owner characteristics in Appendix Table A5 to determine whether the disparate ticketing patterns documented above largely accrue to individuals whose home neighborhood matches the racial composition of the ticketing zip code or if the results we find largely reflect commuter traffic instead. The first row of each panel ("main") reproduces the sticker ticket results from Table 3. We then replace each outcome $Y_{it}$ with $Y_{it} \times (Black_i)$ in the second row and $Y_{it} \times (1 - Black_i)$ in the third row, effectively decomposing the differential outcomes in Black neighborhoods to drivers from Black and non-Black neighborhoods, respectively.[22] Across nearly all outcomes, regressions, and ticketing agencies, we find that the burden of the disparate ticketing patterns

[21] Appendix Figure A4 and Appendix Table A4 find broadly similar results but replace the zip code fixed effects with tract fixed effects and redefine neighborhoods as majority-Black at the tract level using the same 75% threshold.

[22] We note that since not all of our tickets contain owner address information, the sum of the two disaggregated point estimates need not add up to the main results. Nevertheless, we view this decomposition as useful in confirming the population facing disparate ticketing.

in Black neighborhoods tends to fall on owners who are also from Black neighborhoods.

### 5.2 Examining Potential Mechanisms

Our results thus far suggest that the marginal sticker ticket is more likely to be written in a Black neighborhood, both in a compositional and level sense and that this pattern is driven almost entirely by CPD rather than non-CPD behavior. Below we explore several potential mechanisms behind these results.

*Departmental Incentives:* An implication of the different responses across ticket-writing departments is that the underlying performance evaluation scheme induces differential responses to the policy. Put differently, since PEA agents are evaluated on their ticket volume, their ticket-writing behavior was already maximizing ticket volume while minimizing search costs. In contrast, CPD officers face no such volume-based incentives to our knowledge. Thus, post-policy change, the marginal benefit of writing an additional sticker ticket, from a revenue collection standpoint, has increased. As a result, officers may induce greater search efforts into finding or ticketing vehicles without appropriate city stickers. Under this interpretation, the disparate patterns we document above are directly viewed as disparate enforcement as part of a broader revenue collection effort, rather than differential compliance.[23]

We partially test whether officers exert greater search effort into finding vehicles with expired stickers by plotting the number of sticker tickets issued by day for 2011 and 2012 in Appendix Figure A6. If officers exert greater search effort, then we would expect to see increases in ticketing frequency immediately after the 15 day sticker ticket renewal grace period ends. In Panel A, we see exactly this pattern for CPD, with a large spike in sticker tickets written on the day the grace period ends. Comparing the change between 2011 and 2012, sticker ticket volume increases by a dramatic 49.5% on the day immediately following the grace period.

In contrast, non-CPD agencies (Panel B) exhibit only a 17.0% increase in sticker ticket volume.[24] Interestingly, we also see small ticket volumes in the days preceding the end of the

[23]To the extent vehicles in Black neighborhoods are more likely to be parked on the street or visible to the average patrol (e.g., Sanchez and Ramos 2018), then Black neighborhoods may see differential levels of sticker enforcement even in the pre-reform period since Black neighborhoods exhibit a lower marginal search cost for sticker-less vehicles. So long as parking patterns do not also differentially change before and after the budget reform, these results may be viewed as holding the marginal search costs fixed by neighborhood while changing the marginal benefit of ticket-writing. We find no evidence that CPD differentially changed the share of tickets issued in parking areas in Appendix Figure A5.

[24]The cyclical pattern in non-CPD ticket volume is a weekend/weekday effect. Therefore, we compare ticket volume on the first weekday after the grace period in 2011 (two days after it ends) against the initial

grace period, although an expired sticker should technically not be subject to enforcement in this window. We note in passing that the share of sticker tickets written in the expiration-grace period window is smaller for non-CPD agencies (<1%) than CPD agencies (between 4.9 - 5.6%), which we take as suggestive evidence of ex-ante ticket writing optimization by the former.

Finally, for completeness, we also show the same histograms for non-sticker tickets and find little evidence of similar discontinuous behavior for this subset of tickets. This empirical pattern suggests that the behavior of CPD officers is more responsive to the reform, perhaps as part of a broader revenue collection effort for the city, and that the behavioral change is in line with what would be expected given the sticker fine increase.[25]

Next, we test how sticker ticket enforcement patterns correlate with alternative neighborhood characteristics. We replace our primary $Black_i \times Post_t$ interaction with different interactions based on pre-reform neighborhood characteristics in Appendix Table A6. If officers are behaving in a purely revenue-maximizing way, then sticker tickets should be written in the areas that have the highest repayment probabilities, such as high-income neighborhoods.[26] In fact, we find the opposite patterns in Column 2.

We also examine the relationship between other policing activity and ticketing patterns for CPD officers. In Column 3, we define crime as the total crimes per 10,000 residents, and the "high crime" indicator includes the zip codes in the upper quartile. The results suggest at least a part of the story is that officers, often located in high-crime areas, begin spending more of their time issuing sticker tickets. In Column 4, we show that CPD officers write more sticker tickets in areas that previously had high rates of sticker tickets (as a fraction of total tickets written in the neighborhood), suggesting that officers are aware of neighborhoods with low sticker compliance rates and alter their search effort accordingly. However, Column 5 shows that fewer sticker tickets are written in neighborhoods with high payment rates. When we test all interactions jointly, we still find that while the coefficient on neighborhood demographics remains large, significant disparities seem to also be significantly associated

expiration day in 2012 in the above calculation.

[25] Appendix Figure A3 shows suggestive evidence of a broader revenue collection effort as CPD also increased their enforcement of non-sticker violations. However, many of the pre-reform estimates are distinctly different from zero, although the differential trend is generally flat. As a result, we interpret this non-sticker ticket evidence with caution but conclude that part of the differential effect may be due to top-down revenue collection concerns.

[26] It's ambiguous whether officers would fully internalize potential ticket contesting or repayment probabilities when comparing the value of a ticket in high and low-income neighborhoods. Higher-income neighborhoods likely have more resources to fight parking tickets, but to the extent officers receive overtime pay for appearing in court (e.g., Chalfin and Goncalves 2021), the marginal ticket in a high-income neighborhood becomes attractive both with respect to repayment probabilities as well as potential private value to the officer.

with area crime characteristics. The alternative channels appear to be less important, at least when defined across all neighborhoods.

We further test for differential officer behavior *within* Black neighborhoods by examining all alternative treatment margins above, but defined within the set of high-Black neighborhoods, as opposed to the overall sample in Appendix Table A7. We find officer behavior that is imperfectly consistent with increased revenue maximization (in response to the incentive). Specifically, sticker tickets are more likely (observably, though imprecise) to be written in high-income Black neighborhoods, compared to low-income Black neighborhoods, a subset which should have *lower* rates of non-compliance, all else equal. Similarly, Black neighborhoods with greater baseline sticker ticket rates experience higher sticker ticket volumes, further suggesting an element of officer knowledge about non-race neighborhood characteristics. However, the vast majority of these tickets are written in Black neighborhoods with lower baseline repayment rates, suggesting some degree of inefficiency with respect to revenue collection. While not statistically significant, Black neighborhoods with higher crime rates also have higher sticker ticket volumes. In sharp contrast, officers in non-CPD agencies exhibit no such disparate patterns, and if anything, go in the opposite direction.[27]

*Differential Compliance:* In this subsection, we investigate how differential car owner compliance with the sticker tax may influence the interpretation of our findings. Concerns over tax evasion have a rich history in the public finance literature (Allingham and Sandmo, 1972). We find evidence of greater aggregate compliance via more purchases and no statistically significant relative change in the rates of sticker purchases in Black zip codes. We find little evidence of evasion in the sense of changes to driver behavior in parking patterns.

One interpretation of our existing estimates is that they simply reflect differences in the ability of drivers to pay for the city sticker. Thus, differential ex-ante compliance with the policy may present itself as disparate ex-post enforcement of the sticker tax if the marginal benefit of writing such a ticket has increased, such that law enforcement agencies are now writing tickets they would not otherwise have in the absence of the budget reform. Alternatively, the 2012 budget reform may have changed compliance rates since it also increased the price of the sticker for both small ($75 to $85) and large ($120 to $135) vehicles. If there is a sufficiently large subpopulation on the margin of sticker purchasing, then such an increase may lead to disparate enforcement as the marginal search cost of finding a delinquent motorist has decreased. While we are unable to measure sticker purchases at the individual level due to data limitations, we conduct several tests to probe how much our estimates may

[27]The contrast between CPD and non-CPD agents is also consistent with differences in outcomes as a consequence of varying incentives across public and private employees in other contexts (e.g., Knutsson and Tyrefors 2022).

reflect differential compliance versus differential enforcement of the policy.

First, we examine neighborhood-level sticker purchasing behavior directly using administrative data on sticker purchases, owner locations, and sticker types from 2008-2016. In Panel A of Appendix Figure A7, we plot event-study estimates of the interaction of year and neighborhood-type indicators, using sticker purchases as the outcome. If there were differential non-compliance with the sticker policy, such that the fine increase induced a large fraction of the non-complying population to suddenly purchase tickets, then we should see greater purchase rates in Black neighborhoods relative to non-Black neighborhoods. Alternatively, the sticker price increase may also lead to a differential reduction in purchasing as marginal individuals are priced out of compliance. If anything, Black neighborhoods have minuscule decreases (38 stickers) relative to non-Black neighborhoods, although we note that the pre-trend estimates are somewhat noisy. However, both groups increased their purchases, as we show below. When we disaggregate sticker purchases into types focusing on passenger vehicles, we find no statistically relative distinguishable differential response. This empirical finding is instead consistent with changes in officer behavior rather than substantial changes in civilian behavior due to price-out non-compliance or incentivized purchasing.

Car owners may also alter their parking behavior in an attempt to avoid enforcement. Enforcement may vary based on parking location. We can (with some noise) measure whether a ticket was issued in a parking lot or structure. To do so, we measure whether a sticker ticket was issued at a location classified by Open Street Maps as a parking amenity.[28] 3.3% of CPD sticker tickets are issued in parking amenities (4.1% in non-Black zip codes, 2.2% in Black). 4.5% of non-CPD sticker tickets are issued in parking amenities (5.3% in non-Black zip codes, 1.6% in Black).[29] We map this in Appendix Figure A1.

While not a perfect test for car owner behavior, Appendix Figure A5 shows that the share of tickets issued by CPD in parking areas does not substantially change in Black zip codes relative to white zip codes after the policy change. This is evidence that drivers in white areas are not only changing their parking behavior in order to avoid more costly enforcement. The patterns in Appendix Figure A5 are instead consistent with increased search effort from CPD.

*Quantifying the Contributions of Differential Compliance and Enforcement:* The increase in disparate sticker ticketing is due to two potential factors - differential sticker purchasing

[28]See https://wiki.openstreetmap.org/wiki/Tag:amenity=parking for details on how Open Street Map classifies parking amenities.

[29]Mapping tickets into parking areas is done with some noise, as the ticket latitude and longitude are often for the street address rather than within the parking area. Thus, we impose a buffer, and a ticket is deemed "in a parking amenity" if it occurs within 15 meters from a parking amenity or within a parking amenity as defined by Open Street Mapping. Results are robust to alternative buffer regions, even at a buffer of 30m, fewer than 9% of sticker tickets are in parking amenities.

behavior and differential enforcement of the sticker ticket. In Table 4, we decompose this aggregate effect into its two component channels based on our empirical results, in addition to the within-neighborhood changes for Black and non-Black zip codes. We focus on the neighborhood-level (as opposed to analysis at the ticket level) as they capture both the extensive and intensive ticket-writing margins.

We first estimate the share of vehicles in the pre-reform period that are unregistered as of the end of the grace period, finding that around one-fifth of vehicles are unregistered, though our measure of total vehicles contains sampling error. We then apply estimates of within-neighborhood CPD enforcement and purchasing responses to estimate the share of the unregistered vehicle stock that is affected by the reform. Specifically, we construct the within-neighborhood change as a simple one-way difference and divide these changes by the estimated stock of unregistered vehicles. Strikingly, we find that over two-thirds of estimated unregistered vehicles are subject to enforcement in Black neighborhoods, whereas non-Black neighborhoods face no such increase in enforcement, despite having a similar number of unregistered vehicles. These empirical patterns are not explained by changes in purchasing behavior as both Black and non-Black neighborhoods have similarly sized increases in compliance, nor are they fully explained by baseline differences in compliance as the implied enforcement level more than closes the level gap in the number of unregistered vehicles. Thus, the differential ticketing increase in Black neighborhoods is predominantly driven by changes in enforcement, rather than behavioral responses from drivers or unequal baseline non-compliance rates.

*Is Differential Enforcement Efficient?:* Our results consistently point to Black neighborhoods receiving substantially greater levels of sticker ticket enforcement, in magnitudes that cannot be rationalized by large changes in sticker purchasing behavior. And moreover, this disparate effect is entirely driven by CPD rather than non-CPD ticketing agencies. One rationale for these empirical patterns is that CPD officers are differentially targeting areas with lower sticker purchase rates, while non-CPD officers have already equalized their marginal costs of enforcement across neighborhoods.

To understand how neighborhood responses and baseline characteristics influence enforcement behavior, we construct joint distributions of estimated changes in neighborhood-level ticketing outcomes and baseline neighborhood characteristics.[30]

In Panels A and B of Figure 4, we plot the joint distributions of neighborhood-level changes in sticker tickets and sticker purchases, separately by neighborhood type and ticket

[30]Formally, we consider all one-way differences for $i \in \mathcal{I}$ and $R_i \in \{B, n\}$ of $E[Y_{it}|R_i = r, Post_t = 1] - E[Y_{it}|R_i = r, Post_t = 0]$, which represent each component piece of our difference-in-differences estimates. Averaging across all of these estimates by neighborhood type $R_i$ recovers our main DiD estimates.

issuing agency. There is a weakly positive correlation between changes in sticker purchases and CPD-issued sticker tickets in non-Black neighborhoods, which is sharply contrasted with a negative relationship in Black neighborhoods (Panel A). Strikingly, non-CPD-issued sticker tickets display parallel and virtually flat relationships across neighborhood types (Panel B). One interpretation for these contrasting patterns is that CPD issuers are responding to the ticket increase incentive by increasing search behavior in neighborhoods with low marginal search costs, while non-CPD agents have already equated the marginal enforcement costs across areas.[31] Perhaps more noteworthy is the consistent level difference in sticker ticket volume by neighborhood type in Panel A across nearly all changes in sticker purchases.

We further explore whether differences in neighborhood characteristics can explain the gap. In Panel C, we test whether differential pre-reform sticker purchase rates can rationalize such a gap, but we continue to find a persistent level difference, with virtually all neighborhood purchase rates clustered closely around one.[32] Alternatively, such a disparity may be justified by revenue collection motivations if the repayment probabilities are higher in Black versus non-Black neighborhoods. However we find that sticker ticket volumes are higher in Black neighborhoods, despite having lower pre-reform sticker ticket payment probabilities (Panel D). Finally, we show that changes in ticket volumes remain higher in Black neighborhoods across almost all values of sticker tickets and paid sticker tickets per sticker purchase (Panels E and F), indicating sharply distinct enforcement responses across areas with similar baseline enforcement propensities. One additional possibility is that the CPD-issued sticker tickets are incidental because an officer happened to be in the area and there is an increased emphasis on issuing these tickets. We test this channel in Appendix Figure A8, plotting neighborhood-level changes in sticker ticket volumes against average annual crimes reported to CPD. Consistent with this mechanism, we find greater sticker ticket responses in higher-crime neighborhoods. In contrast, we find non-CPD behavior that is either uncorrelated or related in the opposite direction. Reassuringly, we also find no differential changes in crime or police activity across neighborhoods around the time of the reform (see Appendix Figure A9). Together with our investigation of other mechanisms, we view this incidental channel as complementary at differentially lowering marginal costs of enforcement for CPD officers.

Taken together, we conclude that observable differences in neighborhood characteristics, compliance, and expected payment probabilities are insufficient to fully explain the sticker

[31] A possible interpretation of the negative slope is that CPD agents are more successfully capturing every marginal change in sticker purchases - perfect enforcement would suggest a slope of -1. We estimate a slope coefficient of -0.52. However, this slope difference does not explain the level difference between neighborhoods with similar purchase responses.

[32] Some of the x-axis dispersion is likely due to measurement error in the number of vehicles since we rely on aggregated survey-based measures when constructing this statistic.

ticketing gap across Black and non-Black neighborhoods. Instead, our results are consistent with a differential response to the fine increase by ticketing agency, combined with differential marginal search costs across neighborhoods that are not explained by differential access to parking structures. Therefore, the interaction of incentives and search costs together plays a role in determining disparate enforcement patterns.

Given the overlap in the support of non-race neighborhood characteristics, there are potentially significant revenue gains from equalizing enforcement across Black and non-Black neighborhoods. A partial back-of-the-envelope calculation leveraging the joint distributions of neighborhood characteristics and neighborhood responses suggests that the city could have raised an additional \$1.9 million in annual revenue by applying average equal enforcement in low-compliance non-Black neighborhoods.[33]

## 6 Estimating Officer-Specific Responses

Our aggregate event study results reveal disproportionate issuance of sticker tickets across neighborhoods. An open question is whether this disparate behavior is department-wide or if it is concentrated among a handful of officers who are high-volume ticket-writers. We estimate a modified version of our difference-in-differences specification above to decompose the response to the policy reform across the officer distribution. Formally, we estimate:

$$Y_{ijlt} = \underbrace{\sum_{j \in J} \delta_j (Z_j \times Post_{lt})}_{\text{Officer-specific responses}} + \underbrace{Z_j}_{\text{Officer fixed effect}} + \mathbf{X}'_{it}\pi + \nu_{ijlt} \tag{3}$$

for neighborhood $i$, officer $j$, ticket $l$, and year $t$. We control for year, unit, neighborhood, and officer fixed effects.[34] We study racial differences in officer ticketing by interacting $Y_{ijt}$ with indicators for neighborhood racial composition instead of placing the interaction term on the right-hand side.

The coefficients of interest are the interactions $\delta_j$, which, conditional on the officer fixed

[33] To perform this calculation, we first identify non-Black neighborhoods with lower purchase per vehicle rates than the minimum rate of Black neighborhoods. Intuitively, these are the neighborhoods where non-compliance is highest, and the marginal cost of enforcement is consequently lowest (abstracting from parking patterns). We then assign the mean Black neighborhood enforcement volume to these neighborhoods and assume the payment probability is equal to the pre-period payment rate. The mean payment rate for these focal non-Black neighborhoods is 59.5%, relative to 46.9% in Black neighborhoods.

[34] These fixed effects account for time-invariant differences in responsibilities and ticket writing potential across both unit assignments and geography. We depart slightly from our aggregate analysis and use tract (rather than zip) fixed effects and racial composition to more closely approximate officer beat assignments. These modifications allow us to identify racial differences in policy response within all officers rather than only among the subset of officers whose assignment happens to be near zip code boundaries.

effects, nonparametrically capture the within-officer response to the change in incentives induced by the fine increase. When estimated at the sticker level, $\delta_j$ can be interpreted as the officer-specific outcome of the marginal ticket written in response to the policy.[35] Our estimates of officer-specific responses may not exactly match either the ticket- or area-level event studies above as we have both altered the sample by trimming only pre or only-post-period officers as well as the estimating equation.This exercise characterizes the behavioral response across the officer distribution.

### 6.1 Decomposing Outcomes of Marginal Sticker Tickets

Figure 5 reports the distributions of officer-specific policy responses. In Panel A, we plot bins of the officer-specific probability of writing a sticker ticket separately for Black and non-Black neighborhoods against the overall officer-specific sticker ticket response ($P(sticker|ticket, race)$ against $P(sticker\,|\,ticket)$).[36] This exercise effectively decomposes the marginal sticker ticket response outcomes within each officer. Comparing the slopes of the race-specific against the overall response yields similar conclusions to our aggregate event studies above - officers responding to the policy reform are substantially more likely to write sticker tickets in Black neighborhoods than non-Black neighborhoods (0.641 vs 0.359). The magnitude of the overall sticker ticket response on the x-axis also provides evidence of a "first-stage" response to the policy, as greater than 65% of officers are more likely to write a sticker ticket post-reform.[37]

Panel B examines the officer-specific revenue responses accruing from payment sticker tickets. The correlations between the race-specific and overall responses suggest that over 60% of the revenue originates from Black neighborhoods. Together with our decomposition results, these correlations suggest that the unequal enforcement of the sticker ticket also led to an unequal tax burden across neighborhoods.

In Panels C and D, we decompose the outcomes of the marginal sticker ticket separately for Black (Panel C) and non-Black (Panel D) neighborhoods. Specifically, we plot the correlations between $P(ticket\ outcome \mid sticker, race)$ against $P(sticker \mid race)$. There are striking differences in sticker ticket outcomes across race. Under 35% of sticker tickets written in Black neighborhoods end in payment, compared to non-Black sticker tickets, which are almost 15 p.p. more likely to end in payment. Sticker tickets in Black neighborhoods are significantly more likely to end in financial strain, consistent with our aggregate results

[35] We restrict the sample to officers who write at least 100 tickets in our sample period and write tickets both before and after 2012 to alleviate noise concerns. These restrictions drop only a handful of officers. We cannot conduct a similar exercise for non-CPD units due to higher rates of turnover in those departments.

[36] We also report Empirical Bayes-adjusted estimates in Appendix Figure A10.

[37] A version of this exercise which captures both the extensive and intensive margin, reveals that over 85% of officers are responsive in a "first-stage" sense, providing additional support of behavioral changes to the policy reform across the officer distribution.

above. Fully 45.3% of sticker tickets either receive a notice of non-payment (39.7%) or end in the driver filing for bankruptcy (5.6%). While sticker tickets in non-Black neighborhoods also only end in payment about half the time, there are fewer adverse financial outcomes (23.2% notice, 1.3% bankruptcy). Taken together, our results align with our aggregate analysis that the marginal sticker ticket is more likely to occur in Black neighborhoods, disproportionately generates revenue from this population, and leads to substantially worse financial outcomes compared to non-Black neighborhoods, and that these effects are widespread across the officer distribution.[38]

### 6.2 Correlating Policy Responses with Officer-Level Observables

Finally, we explore whether the magnitude of the disparate sticker response is correlated with officer-level observables. While the majority of officer responses indicate that they are responsive to the sticker ticket fine increase in a first-stage sense, understanding whether officer characteristics are predictive of the magnitude of observed responses is important for characterizing how different types of officers react to incentive changes, as well as for designing department-level policies which may mitigate such adverse incentive responses.

A simple explanation for our officer-level decomposition is that the responses reflect the demographics of the unit that they are assigned to. That is, officers assigned to units with greater Black population shares should also exhibit larger Black ticketing responses. Conversely, officers assigned to units with smaller Black population shares should exhibit larger non-Black ticketing responses. We test whether this mechanism drives our results in Appendix Figure A11, regressing race-specific $\delta_j$ responses against their modal unit assignment's Black share of the population.[39] Consistent with neighborhood demographics playing a key role in determining the responses in Black neighborhoods, we find a strong, positive correlation between estimates of $\delta_j(Sticker, Black)$ and neighborhood demographics. In sharp contrast, however, we find a muted correlation between estimates of $\delta_j(Sticker, Non-Black)$ and neighborhood demographics, rather than a negative correlation, which a pure neighborhood characteristics story would predict.

Given this stark contrast, we next examine whether officer observables predict their policy responses in Table 5, controlling for modal unit fixed effects throughout.[40] In each

[38]The disparate marginal revenue result in Panel B despite the lower payment rate in Panel C is likely driven by increases by racial differences in accrual and payment of late fees and extra penalties. Regressing the revenue received against the paid ticket probabilities reveals that the marginal paid Black sticker ticket generates $278 of revenue compared to $236 from non-Black sticker tickets.

[39]We restrict the sample to police officers who are in patrol units so that we can correctly estimate the Black population share in the assignment, as well as examine responses of police officers who are most likely affected by the policy.

[40]We show the correlations using the complete set of officers in Appendix Table A8.

successive column, we test a series of covariates before pooling them all together in Column 4. Black officers consistently have smaller $\delta_j(Sticker, Black)$ responses, along with more experienced officers, though this latter correlation dissipates in Column 4. In contrast, officer characteristics are generally uncorrelated with $\delta_j(Sticker, Non - Black)$, with the exception of ticket volume. These estimates suggest some degree of differential leniency or search effort based on the interaction of officer race and neighborhood demographics. The magnitudes of the $\delta_j$ responses in Black neighborhoods are declining with experience, which is also indicative of early career officers perhaps being more responsive to revenue collection efforts in ways that disparately impact the population.

More generally, the combination of a strong policy response across the officer distribution and weak correlations with observable characteristics suggests that the empirical patterns we find in this paper result from a broader goal of revenue generation on a department-wide level. Given the disparate impacts in the population that clearly hinge on ticketing agency, revenue collection as one responsibility of law enforcement agencies may benefit from specialization.

## 7 Conclusion

In this paper, we examine the role of policing on the distribution of tax burden on residents by exploiting the fine increase for vehicle registration non-compliance in Chicago. Using this sharp change in 2012, we showed that enforcement of this fine was indeed disproportionately distributed in the population, with Black neighborhoods experiencing far greater changes in their ticket volumes than non-Black neighborhoods.

Interestingly, we only find significant evidence of disparate enforcement when examining the ticketing behavior of police officers in the Chicago Police Department and not from tickets issued by parking enforcement agents. We hypothesize that the different responsibilities across the two types of agents generate their differing responses to the policy. Specifically, the narrowness of parking agents' objective function (i.e., to solely maximize ticketing productivity) compared to the large responsibility set of police officers (i.e., public safety) could play a key role in determining the disparate response across neighborhoods. Moreover, we show that CPD's disparate response patterns cannot be fully explained by differences in baseline non-race neighborhood characteristics, nor justified on collection efficiency grounds. Instead, we provide evidence that the combination of a multi-dimensional objective function (and higher crime rates in Black neighborhoods) with differential marginal enforcement costs by neighborhood drives these disparate responses.

Together, our results provide evidence that revenue generation in local governments may benefit from specialization across collection agencies as a mechanism to mitigate disparate impacts in the local population. While parking tickets, particularly sticker tickets, currently function as a form of regressive tax, cities can implement a more equitable and efficient ticketing regime to improve the current equilibrium by altering the incentives of the ticketing agents or by shifting parking enforcement responsibility to only parking enforcement agents. Either of these could simultaneously achieve more equitable outcomes while also raising additional revenue.

Finally, our results document preliminary evidence of a direct relationship between disparate policing and downstream financial consequences. Notably, the increased enforcement of sticker tickets increased the likelihood of filing for bankruptcy by 1.5 percentage points more in Black neighborhoods relative to non-Black neighborhoods. Thus, policies addressing disparate policing behavior may also reduce racial disparities in socioeconomic outcomes.

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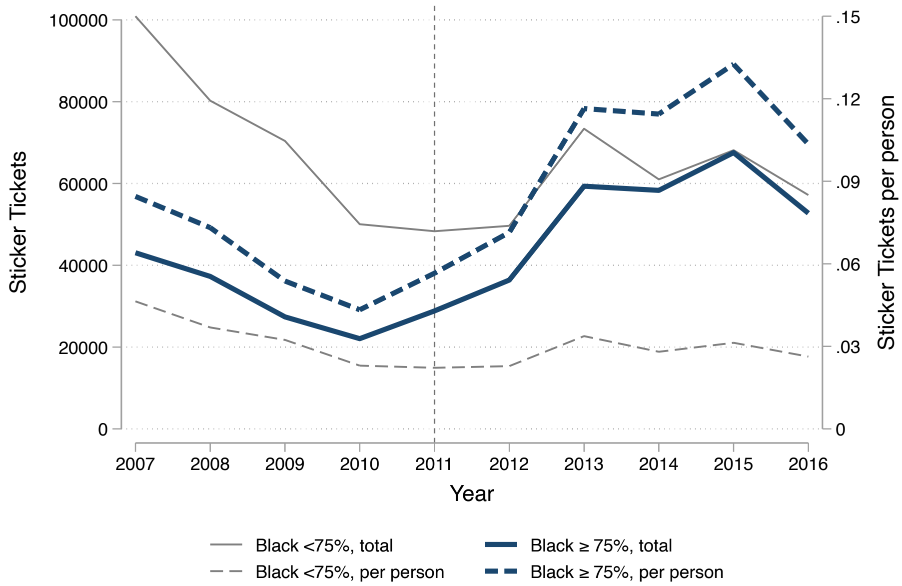
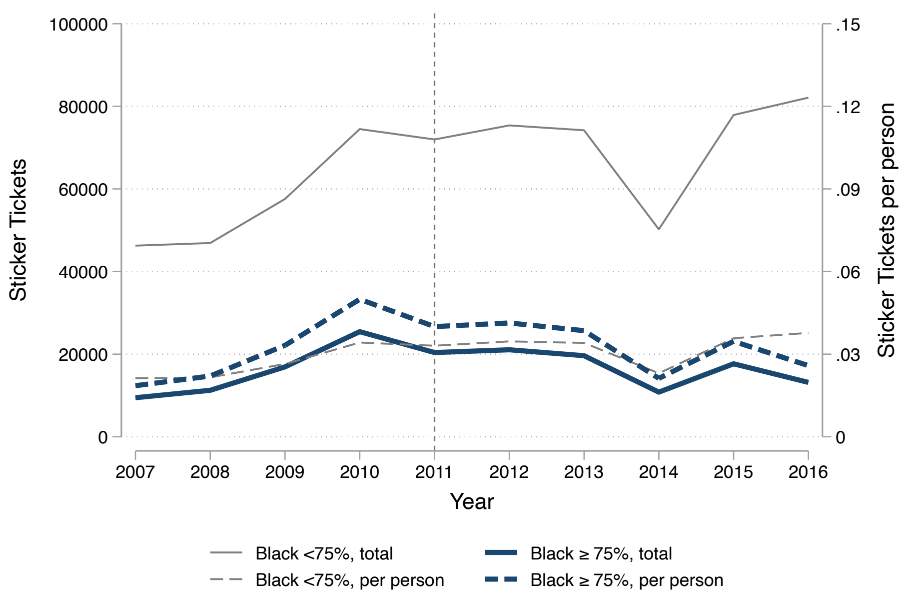
Figure 1: Time Series of Sticker Ticket Volume by Issuing Agency

Panel A: Chicago Police Department

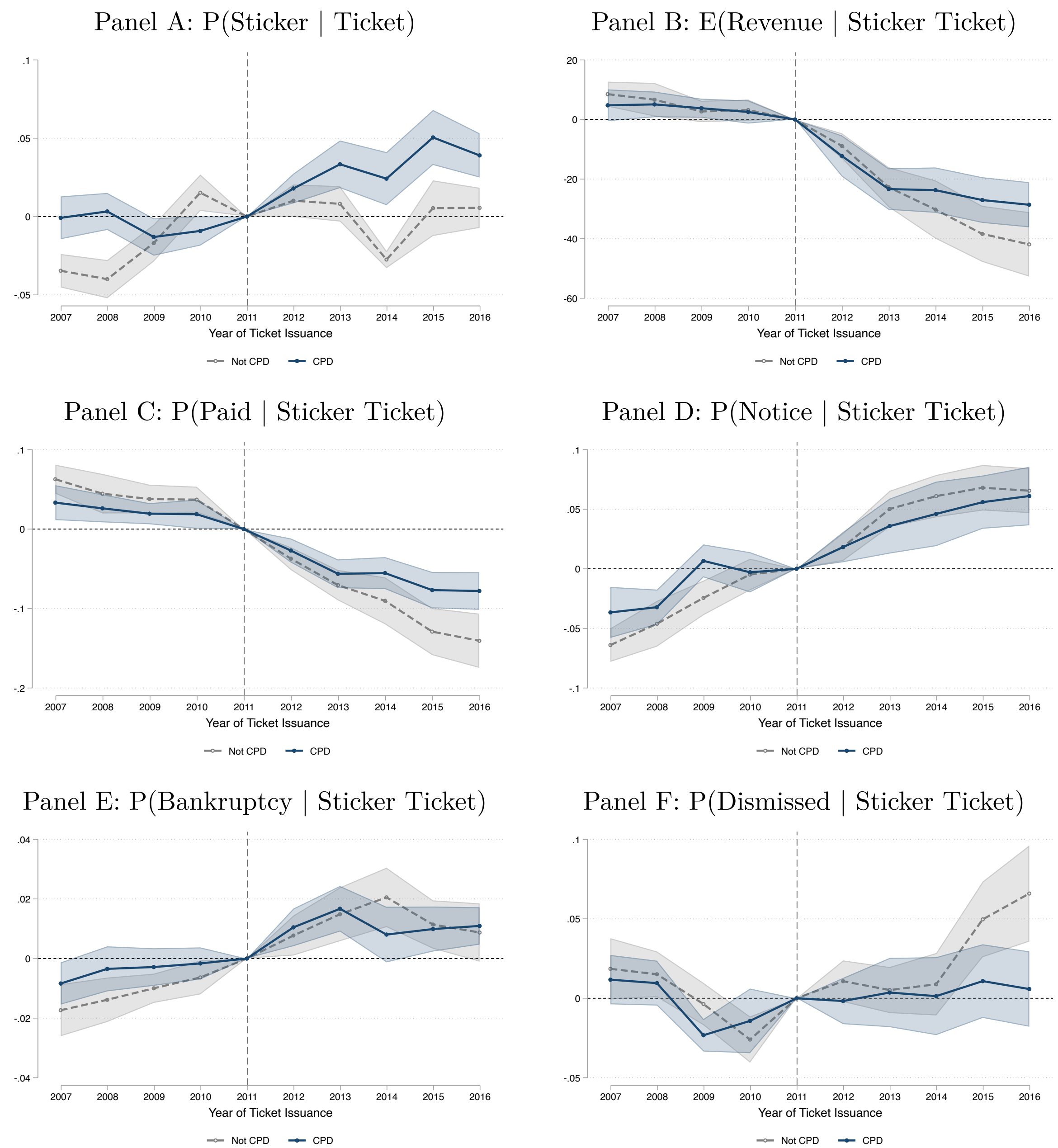



Panel B: Non-Chicago Police Department



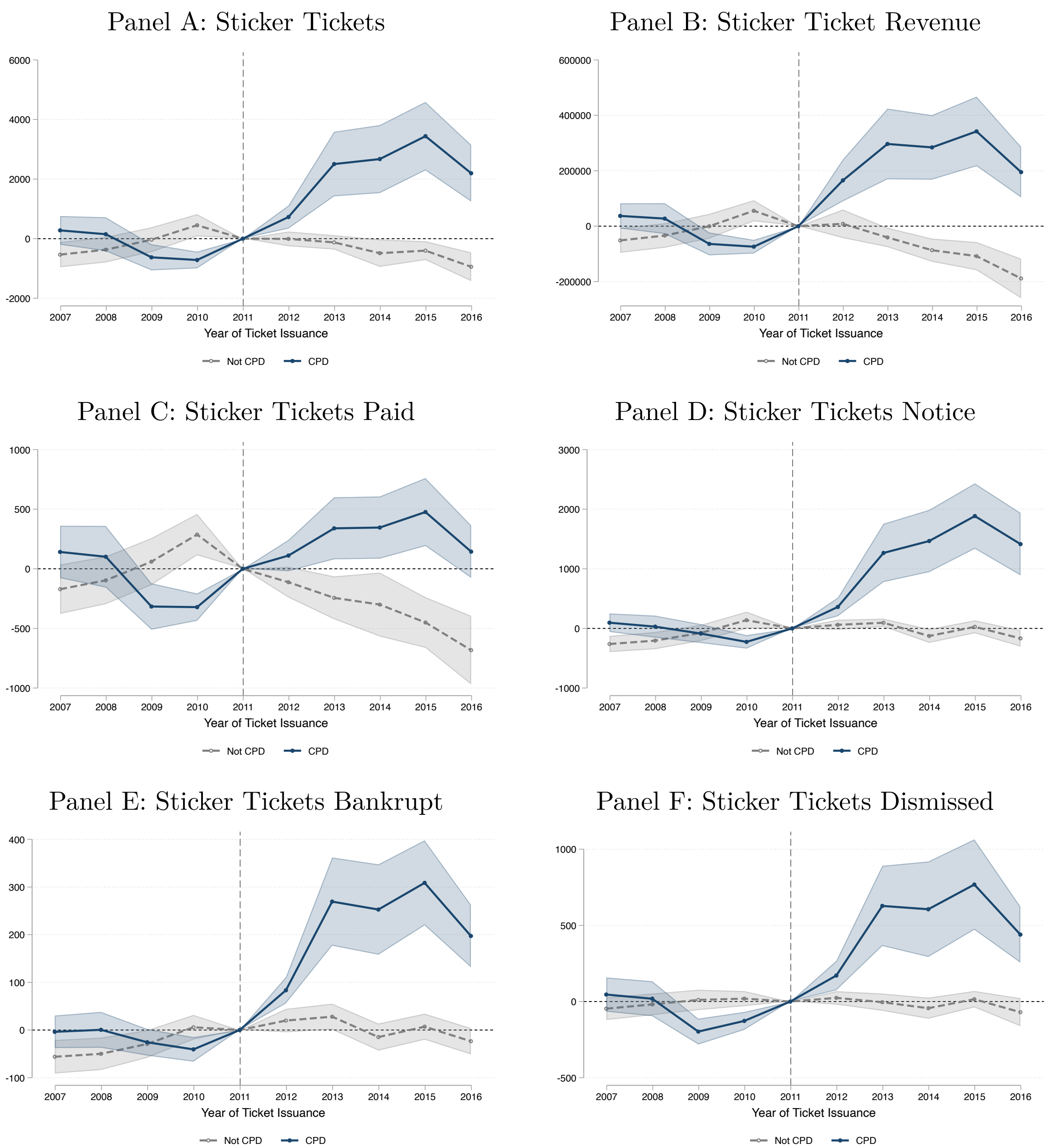

Notes: This figure reports time series of sticker tickets issued and sticker tickets issued per capita by neighborhood and ticketing agency. Black neighborhoods are defined as zip codes with greater than seventy-five percent Black population share. Panel A reports results for CPD and Panel B reports results for non-CPD agencies. Solid lines report levels (left axis), dashed lines report per-capita population rates (right axis). Blue lines represent Black neighborhoods and gray lines represent non-Black neighborhoods. The vertical line in 2011 denotes the last year prior to the reform. Population is measured using the 2007-2011 American Community Survey.

Figure 2: Event Study Estimates of Sticker Tickets and Outcomes at the Ticket-Level by Issuing Agency



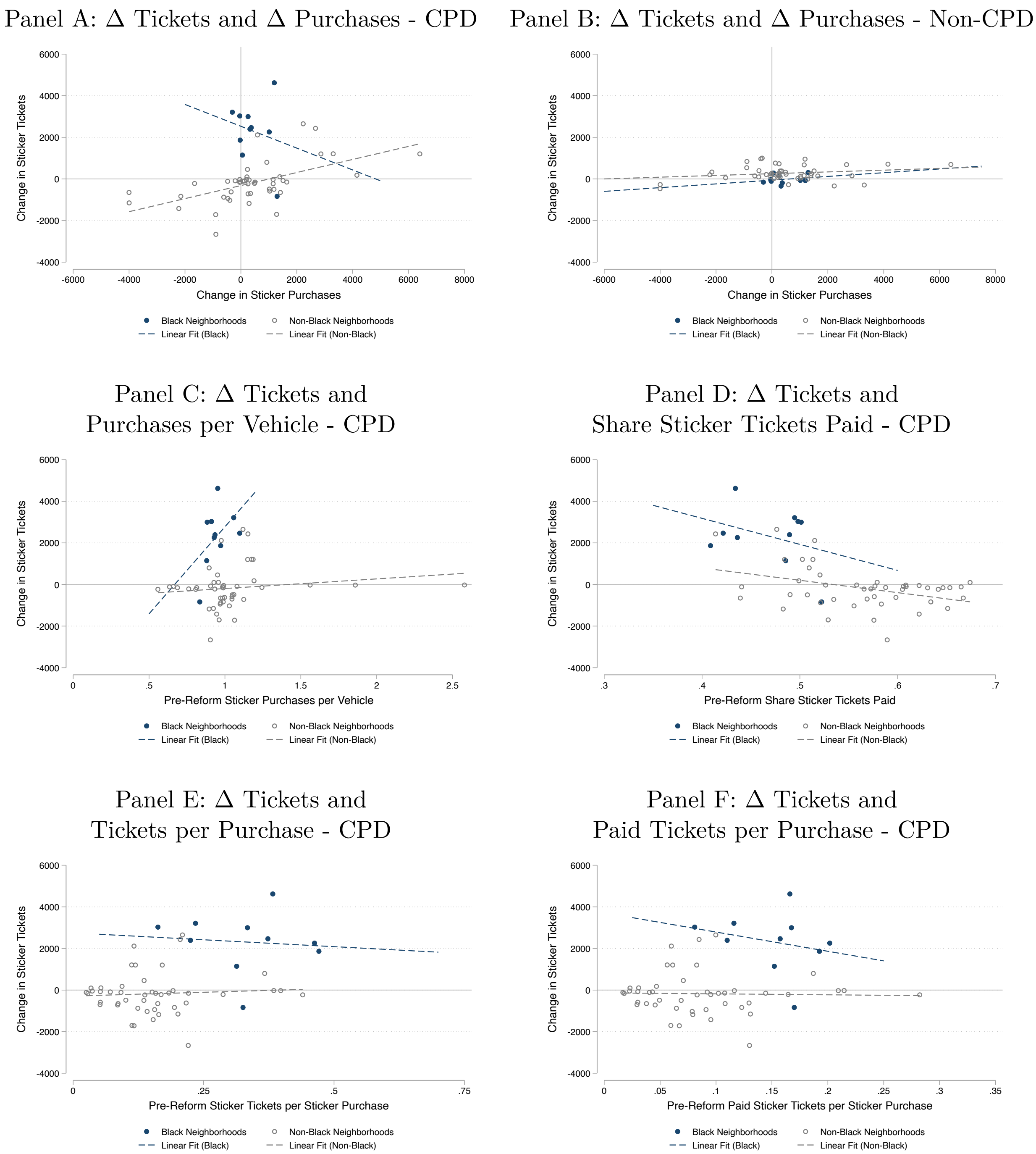

Notes: This figure reports event study estimates of sticker ticketing behavior and sticker ticket outcomes at the ticket level, estimated separately for the Chicago Police Department (CPD) and non-CPD agencies. Each point represents the interaction of $Black_i$ and the corresponding year fixed effect, relative to the level in 2011. The blue points report estimates for CPD and the gray points represent estimates for non-CPD. Shaded regions represent 95 percent confidence intervals with standard errors clustered at the neighborhood level.

Figure 3: Event Study Estimates of Sticker Tickets and Outcomes at the Neighborhood-Level by Issuing Agency



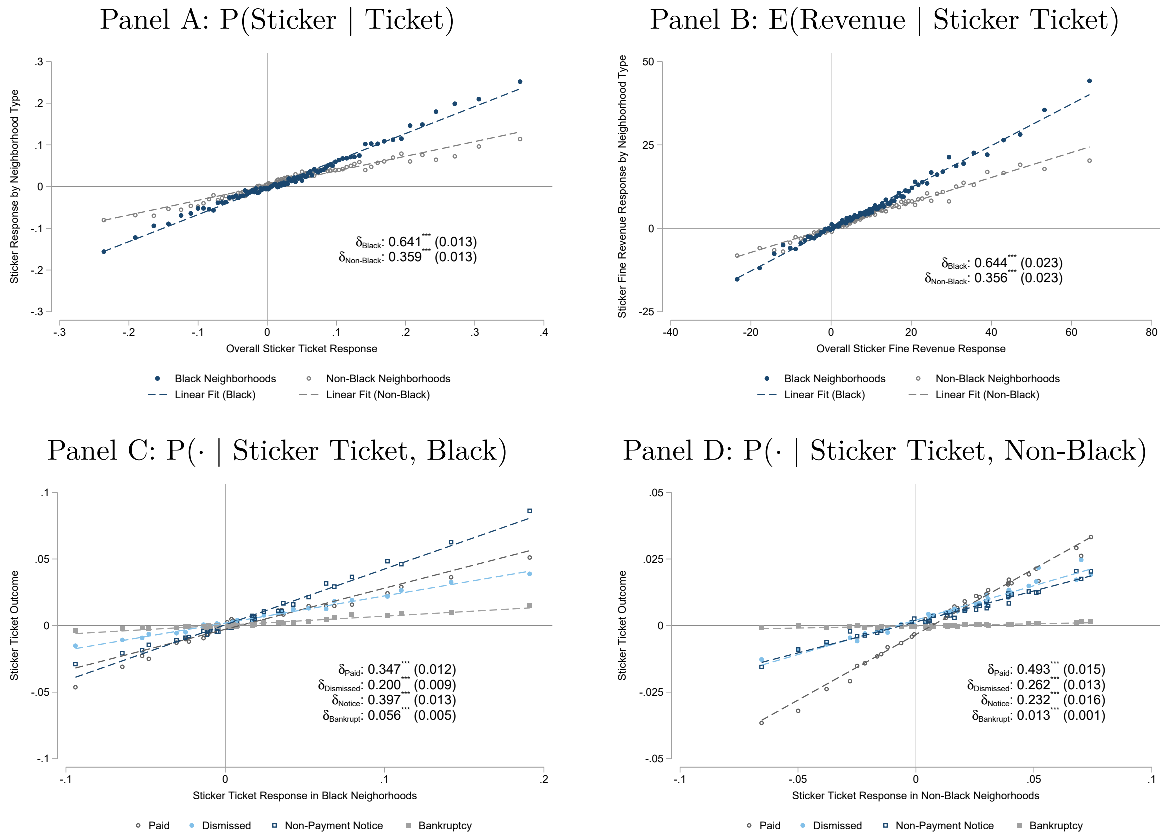

Notes: This figure reports event study estimates of sticker ticketing behavior and sticker ticket outcomes at the neighborhood level, estimated separately for the Chicago Police Department (CPD) and non-CPD agencies. Each point represents the interaction of $Black_i$ and the corresponding year fixed effect, relative to the level in 2011. The blue points report estimates for CPD and the gray points represent estimates for non-CPD. Shaded regions represent 95 percent confidence intervals with standard errors clustered at the neighborhood level.

Figure 4: Joint Distributions of Neighborhood-Level Estimates and Neighborhood Characteristics




Notes: This figure reports joint distributions of neighborhood-level one-way difference estimates across different outcomes, along with neighborhood-level estimates with pre-reform characteristics. Panels A and B plot the change in sticker tickets and sticker purchases for Black and non-Black neighborhoods, by CPD and non-CPD ticketing agency, respectively. Panels C through F plot the change in sticker tickets issued by CPD against pre-reform neighborhood characteristics, calculated using data from 2008-2011. Each point represents a neighborhood, defined at the zip code level. Navy dots represent Black neighborhoods and gray circles represent non-Black neighborhoods. Dashed lines represent linear lines of best fit, estimated separately by neighborhood type.

Figure 5: Estimating and Decomposing Officer-Specific Responses to Sticker Fine Increase




Notes: This figure plots estimates of $\delta_j$ for different outcomes against each other. In Panels A and B we plot estimates of neighborhood race-specific $\delta_j$ responses against the overall race-agnostic $\delta_j$ response on the x-axis. In Panels C and D, we plot the race-specific sticker ticket outcomes against the race-specific sticker ticket responses, separately by race. There are 100 bins per outcome in the top two panels and 40 bins per outcome in the lower two panels. For exposition, we drop the first and last bin for each outcome. Reported coefficients estimated on the underlying officer-level estimates. Robust standard errors are reported in parentheses. *** = significant at 1 percent level, ** = significant at 5 percent level, * = significant at 10 percent level.

Table 1: Annual Volume and Revenue from Top Ten Revenue Generating Tickets in Chicago

| | 2007-2011 | | | | | | 2012-2016 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Tickets (000s) | Revenue ($000s) | Avg. Fine | Rev. Share | Rev. Rank | Rev./ E[Rev.] | Tickets (000s) | Revenue ($000s) | Avg. Fine | Rev. Share | Rev. Rank | Rev./ E[Rev.] |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Expired Meter | 404 | 19,533 | 50 | 0.14 | 1 | 0.97 | 283 | 15,265 | 50 | 0.10 | 4 | 1.08 |
| No City Sticker | 178 | 18,614 | 120 | 0.14 | 2 | 0.87 | 205 | 29,575 | 200 | 0.20 | 1 | 0.72 |
| Expired Plates | 368 | 17,151 | 50 | 0.13 | 3 | 0.93 | 361 | 19,562 | 60 | 0.13 | 2 | 0.90 |
| Street Cleaning | 282 | 14,820 | 50 | 0.11 | 4 | 1.05 | 271 | 15,766 | 60 | 0.11 | 3 | 0.97 |
| Residential Permit Parking | 222 | 12,858 | 60 | 0.09 | 5 | 0.96 | 179 | 13,033 | 75 | 0.09 | 5 | 0.97 |
| Parking Prohibited Anytime | 145 | 8,046 | 60 | 0.06 | 6 | 0.93 | 129 | 9,270 | 75 | 0.06 | 6 | 0.96 |
| Rush Hour Parking | 122 | 7,123 | 60 | 0.05 | 7 | 0.97 | 67 | 5,533 | 100 | 0.04 | 8 | 0.82 |
| Rear And Front Plate Required | 154 | 6,782 | 50 | 0.05 | 8 | 0.88 | 117 | 4,622 | 60 | 0.03 | 10 | 0.66 |
| Park In Transit Stand | 51 | 4,906 | 100 | 0.04 | 9 | 0.95 | 38 | 3,589 | 100 | 0.02 | 11 | 0.95 |
| Within 15' Of Fire Hydrant | 46 | 4,549 | 100 | 0.03 | 10 | 0.99 | 43 | 5,119 | 150 | 0.03 | 9 | 0.80 |

Notes: This table reports average annual characteristics of the top ten revenue generating tickets from 2007-2011 and characteristics for the same set of tickets from 2012-2016. The type of ticket is listed in each row. Columns 1 and 7 report annual ticket volume, Columns 2 and 8 report annual ticket revenue, Columns 3 and 9 report the modal fine amount, Columns 4 and 10 report the revenue share of the listed ticket, along with the revenue share rank in Columns 5 and 11. Columns 6 and 12 report the ratio of revenue received and expected revenue, calculated as the base fine amount times ticket volume. The revenue share is less than one when collected revenue plus applicable late fees is less than the expected collected amount if all written tickets were paid on time, and is greater than one if collected revenue plus applicable late fees exceeds this expectation.

Table 2: Descriptive Statistics by Neighborhood: 2007-2011

| | All Neighborhoods | Black Neighborhoods | Non-Black Neighborhoods |
|---|---|---|---|
| *Panel A: Ticket-Level Outcomes* | (1) | (2) | (3) |
| CPD Written | 0.503 | 0.602 | 0.487 |
| Sticker Ticket | 0.076 | 0.149 | 0.064 |
| Paid | 0.527 | 0.471 | 0.548 |
| Non-Payment Notice | 0.228 | 0.308 | 0.197 |
| Bankruptcy | 0.021 | 0.039 | 0.014 |
| Dismissed | 0.224 | 0.182 | 0.240 |
| CPD Written | 0.572 | 0.655 | 0.541 |
| *Panel B: Neighborhood Level Outcomes* | | | |
| CPD Written | 21,020 | 19,519 | 21,346 |
| Sticker Ticket | 3,176 | 4,842 | 2,814 |
| Paid | 1,674 | 2,280 | 1,542 |
| Non-Payment Notice | 723 | 1,492 | 556 |
| Bankruptcy | 66 | 188 | 40 |
| Dismissed | 713 | 882 | 676 |
| CPD Written | 1,816 | 3,173 | 1,521 |
| Stickers Purchased | 20,301 | 16,409 | 21,147 |
| *Panel C: Neighborhood Characteristics* | | | |
| Share Black | 0.305 | 0.934 | 0.168 |
| Total Population | 47,966 | 50,965 | 47,314 |
| Total Vehicles | 20,425 | 17,320 | 21,100 |

Notes: This table reports descriptive statistics by neighborhood type over the period 2007-2011. Panel A reports mean outcomes at the ticket-level and Panels B and C report mean annual outcomes at the neighborhood level. Column 1 reports overall means, Column 2 reports means in Black neighborhoods, defined as zip codes with a greater than seventy-five percent Black population share, and Column 3 reports means in non-Black neighborhoods. Sticker purchase data covers the period 2008-2011. Outcomes in Panel C are calculated using the 2007-2011 American Community Survey. We approximate total vehicles by aggregating bins based on survey responses and top code the highest bin as representing four vehicles.

Table 3: Difference-in-Differences Estimates of Disparate Ticketing and Ticket Outcomes

| | Tickets | Revenue | Paid | Notice | Bankruptcy | Dismissed |
|---|---|---|---|---|---|---|
| *Ticket-Level Estimates* | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A: CPD* | | | | | | |
| Sticker: | 0.038*** | -27.297*** | -0.082*** | 0.062*** | 0.015*** | 0.005 |
| | (0.007) | (3.709) | (0.011) | (0.011) | (0.003) | (0.008) |
| Non-Sticker: | -0.038*** | -9.989*** | -0.066*** | 0.048*** | 0.011*** | 0.007 |
| | (0.007) | (1.014) | (0.008) | (0.005) | (0.001) | (0.005) |
| *Panel B: Non-CPD* | | | | | | |
| Sticker: | 0.011** | -30.451*** | -0.121*** | 0.071*** | 0.020*** | 0.030*** |
| | (0.005) | (2.919) | (0.010) | (0.006) | (0.002) | (0.007) |
| Non-Sticker: | -0.011** | -3.611*** | -0.038*** | 0.022*** | 0.005*** | 0.011* |
| | (0.005) | (0.821) | (0.008) | (0.005) | (0.001) | (0.005) |
| *Neighborhood-Level Estimates* | | | | | | |
| *Panel C: CPD* | | | | | | |
| Sticker: | 2,490*** | 271,341*** | 363*** | 1,316*** | 236*** | 574*** |
| | (464) | (51,102) | (114) | (222) | (38) | (108) |
| Non-Sticker: | 11,936*** | 576,982*** | 6,593*** | 2,315*** | 353*** | 2,674*** |
| | (1,494) | (78,250) | (903) | (308) | (54) | (355) |
| *Panel D: Non-CPD* | | | | | | |
| Sticker: | -294*** | -77,131*** | -374*** | 58* | 29*** | -9 |
| | (83) | (17,303) | (65) | (34) | (7) | (20) |
| Non-Sticker: | -3,188** | -321,747*** | -2,376** | -159 | -7 | -646*** |
| | (1,402) | (77,362) | (1,119) | (129) | (17) | (189) |

Notes: This table reports DiD estimates of the change in ticketing behavior across neighborhoods by ticket type and ticketing agency, estimated at the ticket level in Panels A and B and estimated at the zip code level in Panels C and D. Each coefficient is from a separate regression and represents the interaction of $Black_i \times Post_i$. Panels A and C report results for tickets written by the Chicago Police Department. Panels B and D report results for tickets written by the Parking Enforcement Authority (Non-CPD). Rows labeled as Sticker report results for sticker tickets and rows labeled as Non-Sticker report results for all other tickets. Column 1 reports the probability a ticket is a sticker or non-sticker ticket or the number of each ticket type in the area-level estimates. Column 2 reports collected revenue, Columns 3-6 report the outcomes of the tickets as bankruptcy, dismissed, paid, or having received a notice of non-payment. All regressions include zip code and year fixed effects. Standard errors clustered at the zip code level are reported in parentheses. *** = significant at 1 percent level, ** = significant at 5 percent level, * = significant at 10 percent level.

Table 4: Decomposing Relative Contributions of Differential Compliance and Enforcement in Sticker Ticketing Gap

| | Black Neighborhoods | Non-Black Neighborhoods | Gap |
|---|---|---|---|
| | (1) | (2) | (1)-(2) |
| Share Vehicles Unregistered | 0.196 | 0.200 | -0.004 |
| Δ Enforcement Share | 0.689 | -0.047 | 0.737 |
| Δ Compliance Share | 0.123 | 0.121 | 0.002 |
| Total Vehicles | 17,320 | 21,893 | -4,574 |
| Unregistered Vehicles | 3,356 | 3,725 | -369 |

Notes: This table calculates statistics describing the size of the unregistered vehicle stock in the pre-reform period, separately by neighborhood type. The first row calculates the share of vehicles without a valid sticker as of the end of the grace period. The number of unregistered vehicles is estimated using the 2007-2011 American Community Survey. We drop a small handful of neighborhoods with negative estimated non-compliance rates due to measurement error in number of vehicles. The second and third rows estimate the share of unregistered vehicles who were affected by the reform, dividing one-way differences in CPD enforcement and consumer purchases by the number of unregistered vehicles. Column 1 reports these estimates for Black neighborhoods, Column 2 for non-Black neighborhoods, and Column 3 reports the difference between Columns 1 and 2.

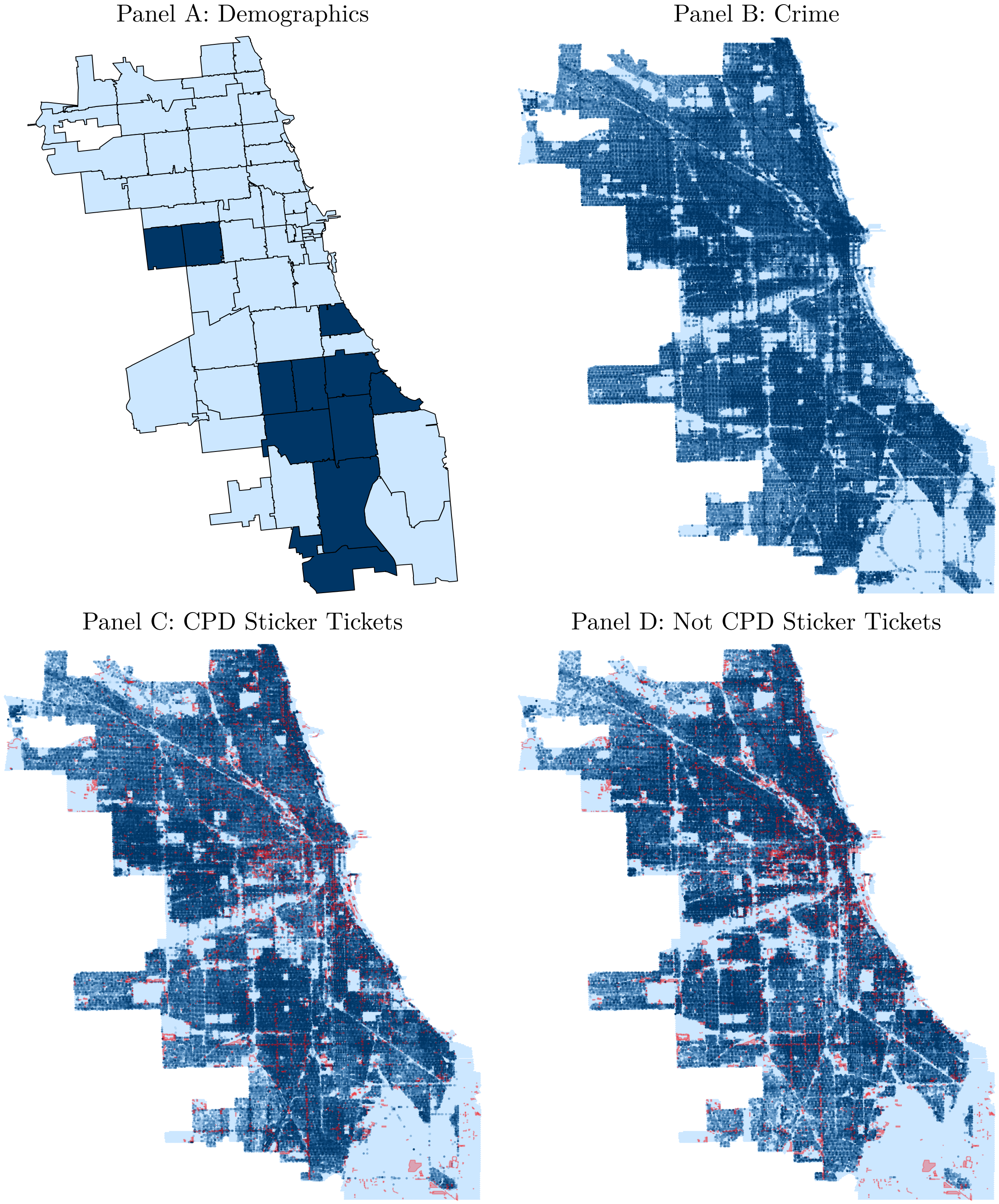
Table 5: Correlating Officer Policy Responses with Observable Characteristics

| | $\delta_j$ Response | | | |
|---|---|---|---|---|
| *Panel A: $\delta_j$ (Sticker, Black)* | (1) | (2) | (3) | (4) |
| Male | -0.000 | | | -0.000 |
| | (0.003) | | | (0.003) |
| Age | -0.000** | | | -0.000 |
| | (0.000) | | | (0.000) |
| Hispanic | | -0.002 | | -0.002 |
| | | (0.003) | | (0.003) |
| Asian or Native American | | -0.001 | | -0.002 |
| | | (0.006) | | (0.006) |
| Black | | -0.009** | | -0.008* |
| | | (0.004) | | (0.004) |
| Years Experience | | | -0.001*** | -0.001 |
| | | | (0.000) | (0.000) |
| Complaints per Year | | | -0.000 | -0.001 |
| | | | (0.002) | (0.002) |
| Tickets Issued per Year (00s) | | | 0.002** | 0.001* |
| | | | (0.001) | (0.001) |
| *Panel B: $\delta_j$ (Sticker, Non-Black)* | | | | |
| Male | -0.000 | | | -0.001 |
| | (0.002) | | | (0.002) |
| Age | -0.000 | | | -0.000 |
| | (0.000) | | | (0.000) |
| Hispanic | | 0.002 | | 0.002 |
| | | (0.002) | | (0.002) |
| Asian or Native American | | 0.010 | | 0.010* |
| | | (0.006) | | (0.006) |
| Black | | 0.001 | | 0.002 |
| | | (0.002) | | (0.002) |
| Years Experience | | | 0.000 | 0.000 |
| | | | (0.000) | (0.000) |
| Complaints per Year | | | 0.001 | 0.001 |
| | | | (0.002) | (0.002) |
| Tickets Issued per Year (00s) | | | 0.001** | 0.001** |
| | | | (0.001) | (0.001) |
| Observations | 4,992 | 4,992 | 4,992 | 4,992 |
| Unit Fixed Effects | Yes | Yes | Yes | Yes |

Notes: This table reports regressions of officer-specific $\delta_j$ responses against officer-level observables. The sample includes only police officers in patrol units. The dependent variable in Panel A is the officer-specific $\delta_j$ for sticker tickets in Black neighborhoods and the dependent variable in Panel B is the corresponding $\delta_j$ for sticker tickets in Non-Black neighborhoods. Experience, complaints and tickets issued per year are all measured prior to the policy change. Robust standard errors are reported in parentheses. *** = significant at 1 percent level, ** = significant at 5 percent level, * = significant at 10 percent level.

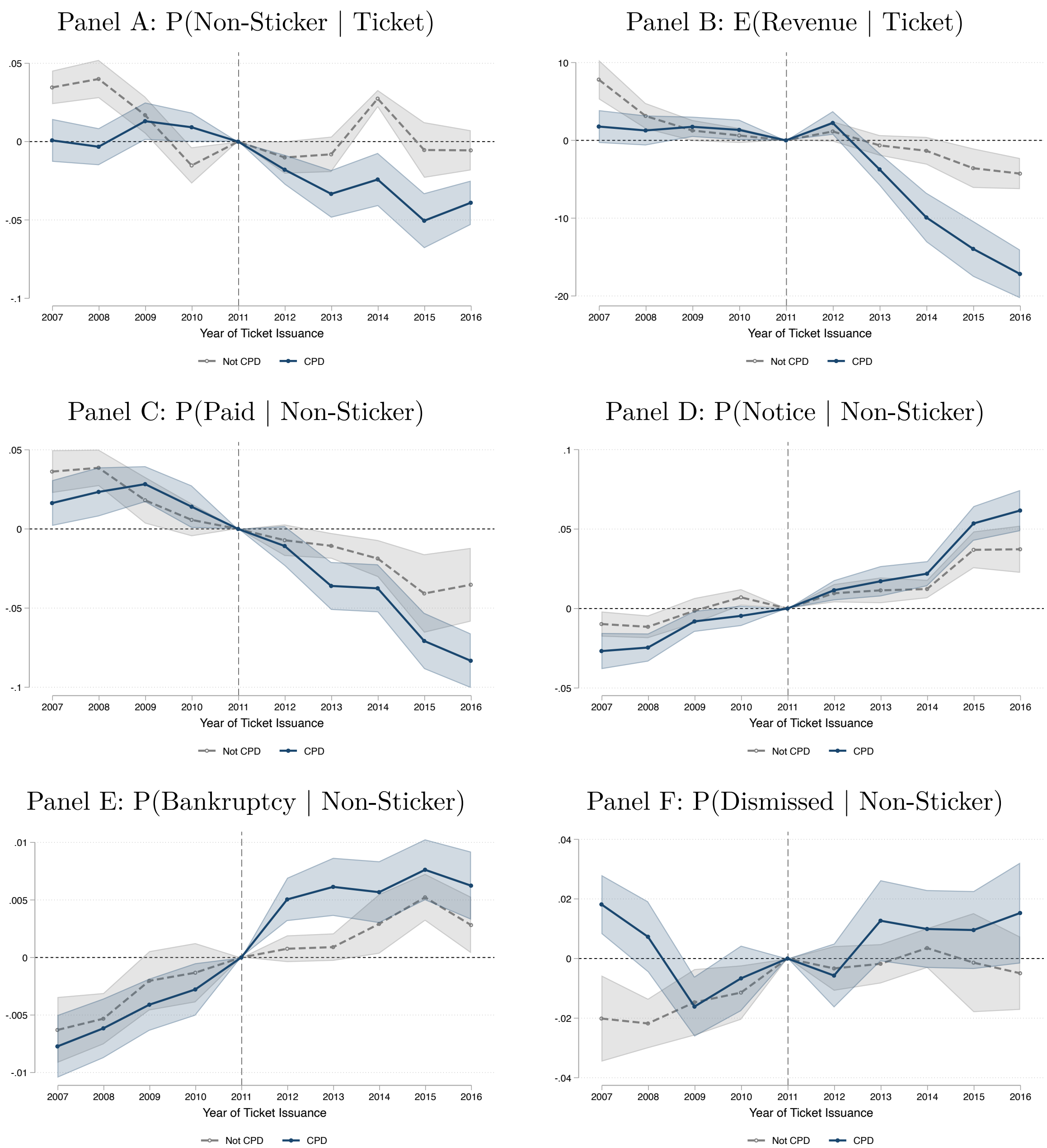
## Appendix A: Additional Results

Appendix Figure A1: Maps of Sticker Tickets, Parking Amenities, Race, and Crime




Notes: This figure reports the geographic distributions of race, crime, CPD sticker ticketing, and non-CPD sticker ticketing. Panel A shows zip codes with greater than 75% of the population reporting their race as Black (from 5 year ACS measures, 2007-2011 and 2012-2016 generate the same figure) in dark blue. Panels B-D discretize Chicago into approximately 100,000 hexagons. Density is estimated with a quartic kernel over a bandwidth of 0.0005, with each color representing a quantile. Red polygons are parking amenities defined by Open Street Map. Panel B shows the distribution of reported criminal offenses with darker Blue areas reporting higher crime.Panels C and D show sticker ticket issuance by CPD and not CPD agents.

Appendix Figure A2: Event Study Estimates of Non-Sticker Tickets and Outcomes at the Ticket-Level by Issuing Agency

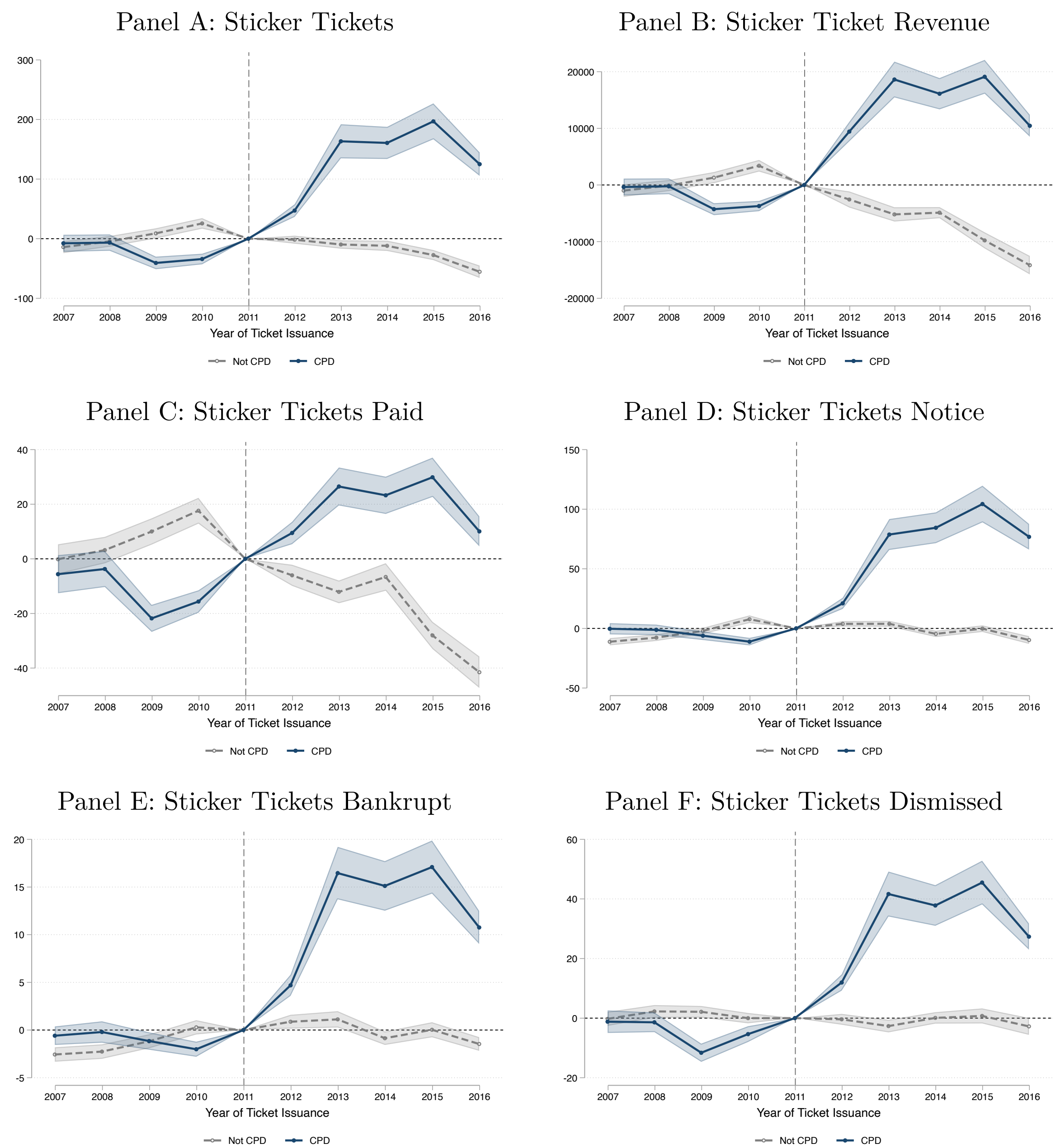



Notes: This figure reports event study estimates of non-sticker ticketing behavior and non-sticker ticket outcomes at the ticket level, estimated separately for the Chicago Police Department (CPD) and non-CPD agencies. Each point represents the interaction of $Black_i$ and the corresponding year fixed effect, relative to the level in 2011. The blue points report estimates for CPD and the gray points represent estimates for non-CPD. Shaded regions represent 95 percent confidence intervals with standard errors clustered at the neighborhood level.

Appendix Figure A3: Event Study Estimates of Non-Sticker Tickets and Outcomes at the Neighborhood-Level by Issuing Agency


Notes: This figure reports event study estimates of non-sticker ticketing behavior and non-sticker ticket outcomes at the neighborhood level, estimated separately for the Chicago Police Department (CPD) and non-CPD agencies. Each point represents the interaction of $Black_i$ and the corresponding year fixed effect, relative to the level in 2011. The blue points report estimates for CPD and the gray points represent estimates for non-CPD. Shaded regions represent 95 percent confidence intervals with standard errors clustered at the neighborhood level.

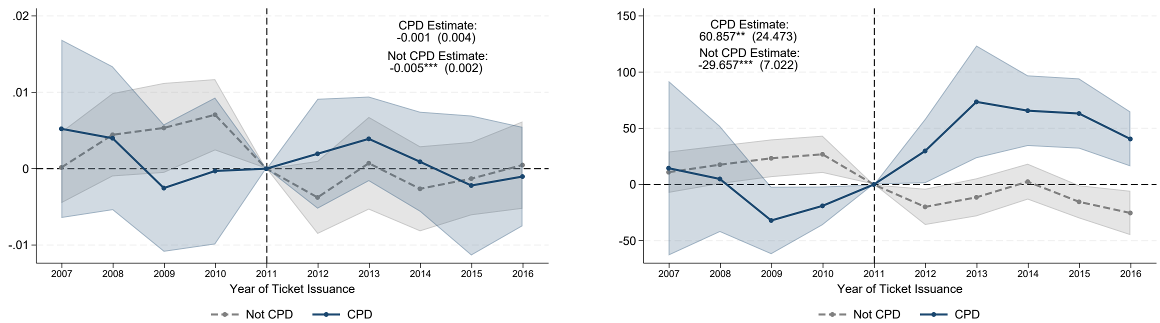
Appendix Figure A4: Event Study Estimates of Sticker Tickets and Outcomes at the Census Tract-Level by Issuing Agency




Notes: This figure reports event study estimates of sticker ticketing behavior and sticker ticket outcomes at the neighborhood (Census tract) level, estimated separately for the Chicago Police Department (CPD) and non-CPD agencies. Each point represents the interaction of $Black_i$ and the corresponding year fixed effect, relative to the level in 2011. The blue points report estimates for CPD and the gray points represent estimates for non-CPD. Shaded regions represent 95 percent confidence intervals with standard errors clustered at the neighborhood level.

Appendix Figure A5: Event Study Estimates of Sticker Tickets in Parking Amenities

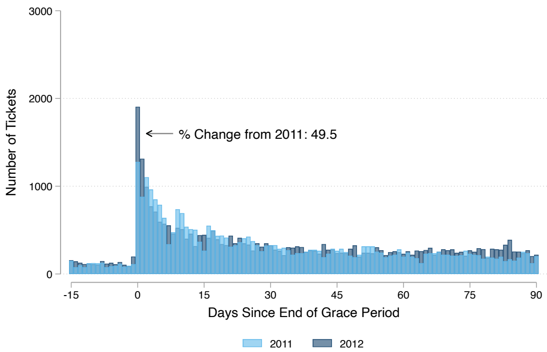
Panel A: P(Parking Amenity | Sticker) Panel B: Parking Amenity Sticker Tickets



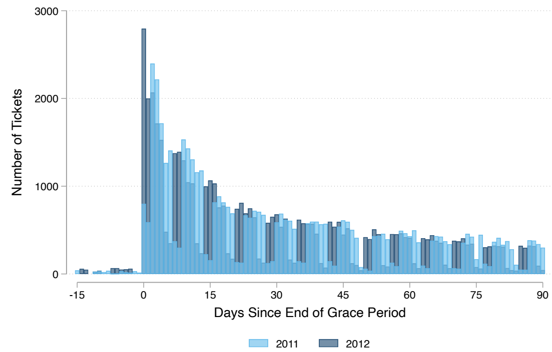

Notes: This figure reports event study estimates of sticker ticketing behavior in parking lots, estimated separately for the Chicago Police Department (CPD) and non-CPD agencies. 3.3% of CPD sticker tickets are issued in parking amenities (4.1% in non-Black zip codes, 2.2% in Black). 4.5% of not CPD sticker tickets are issued in parking amenities (5.3% in non-Black zip codes, 1.6% in Black). A ticket is deemed “in a parking amenity” if it occurs within 0.00013 lat/lon (about 15 meters) from a parking amenity or within a parking amenity as defined by Open Street Mapping. Results are robust to alternative buffer regions, even at a buffer of 0.0002, fewer than 9% of sticker tickets are in parking amenities. Each point represents the interaction of $Black_i$ and the corresponding year fixed effect, relative to the level in 2011. The blue points report estimates for CPD and the gray points represent estimates for non-CPD. Shaded regions represent 95 percent confidence intervals with standard errors clustered at the neighborhood level. *** = significant at 1 percent level, ** = significant at 5 percent level, * = significant at 10 percent level.

Appendix Figure A6: Distribution of Tickets Around the End of Sticker Renewal Grace Period: 2011-2012

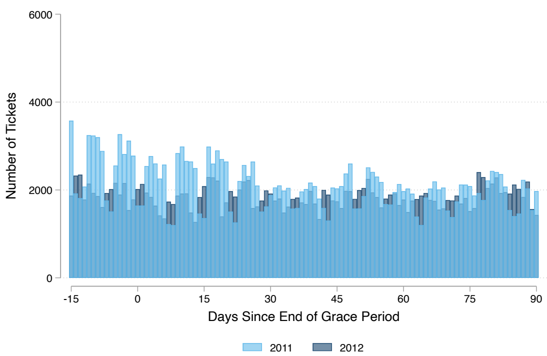
Panel A: CPD Sticker Tickets



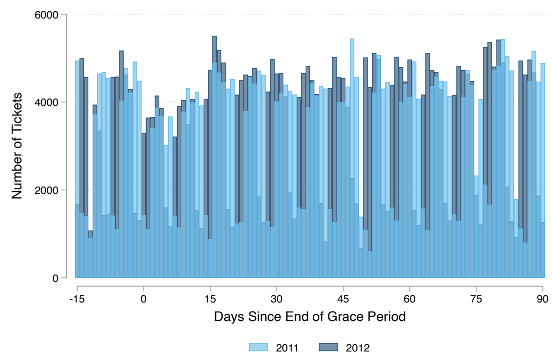

Panel B: Non-CPD Sticker Tickets




Panel C: CPD Non-Sticker Tickets



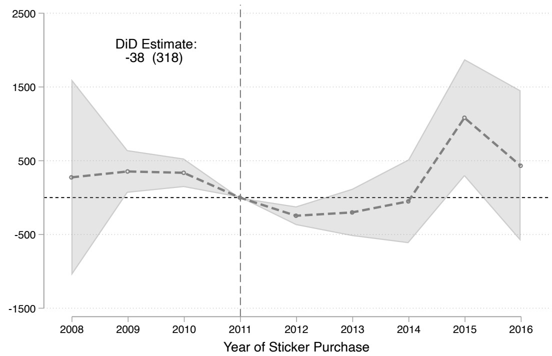

Panel D: Non-CPD Non-Sticker Tickets



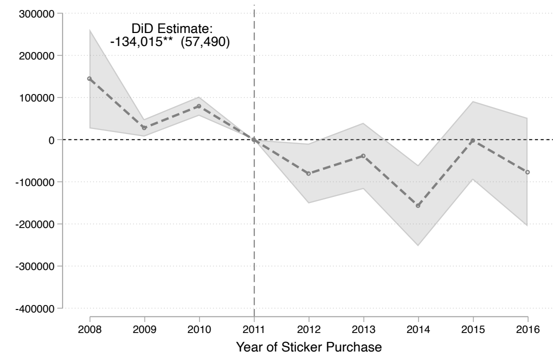

Notes: This figure reports the number of tickets issued per day in 2011 and 2012 by CPD and non-CPD ticketing agencies. Light blue histograms represent 2011 and dark blue histograms represent 2012. The x-axis is normalized to the end of the year-specific sticker renewal grace period and includes 15 days before and 90 days after the end of the grace period. Panels A and C ticketing distributions for CPD and Panels B and D report ticketing distributions for non-CPD agencies. The upper panels report the distribution of sticker tickets and the lower panels report the distribution of non-sticker tickets. The grace period is a window after the expiration date where an individual may purchase a city sticker without paying late fees and is not supposed to be subject to sticker ticket enforcement. We use 2011-2012 as the focal years in this exercise since, prior to 2014, all city stickers expired at the end of June in any given calendar year. The city shifted to time-varying city sticker expiration dates in 2014 when city stickers then expired 6 months after state-level car registration. Moreover, both 2011 and 2012 have the same fifteen-day grace period, which enables us to more cleanly harmonize and compare the data across years.

Appendix Figure A7: Event Study Estimates of Sticker Purchasing Behavior

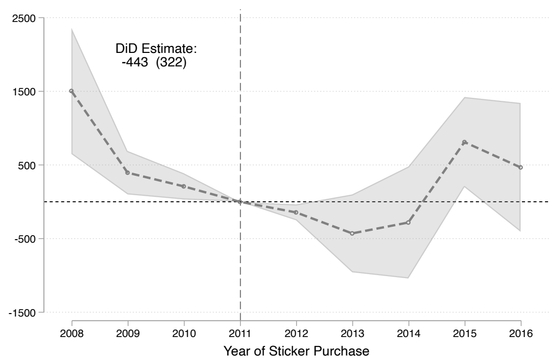
Panel A: Stickers Purchased - All



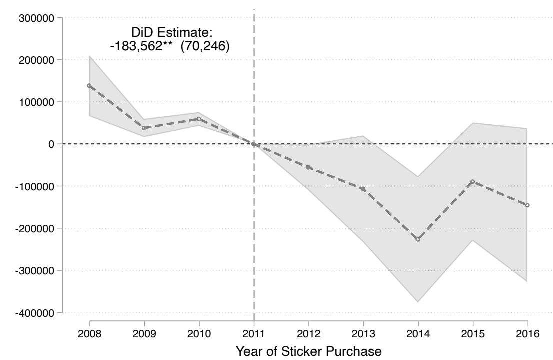

Panel B: Sticker Purchase Revenue - All




Panel C: Stickers Purchased - Passenger



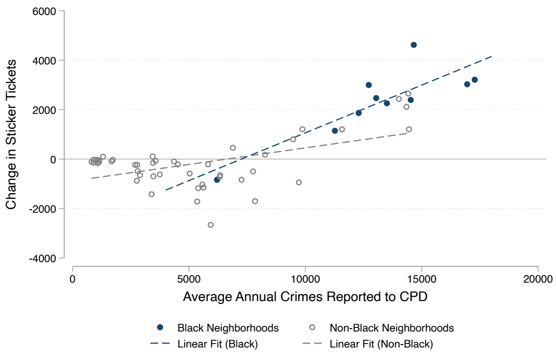

Panel D: Sticker Purchase Revenue - Passenger



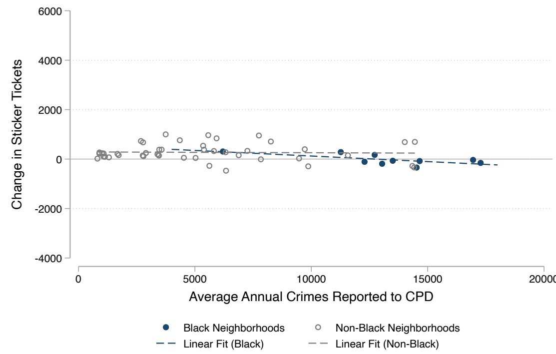

Notes: This figure reports event study estimates of sticker purchases and sticker purchase revenue at the neighborhood level. Each point represents the interaction of $Black_i$ and the corresponding year fixed effect, relative to the level in 2011. All includes passenger, large vehicles, and motorcycles, the latter of which we exclude from the decomposition in the lower panels. Corresponding difference-in-differences estimates are reported in each panel. Shaded regions represent 95 percent confidence intervals with standard errors clustered at the neighborhood level. *** = significant at 1 percent level, ** = significant at 5 percent level, * = significant at 10 percent level.

Appendix Figure A8: Joint Distributions of Neighborhood-Level Estimates and Crime Levels

Panel A: Δ Tickets and Crime - CPD

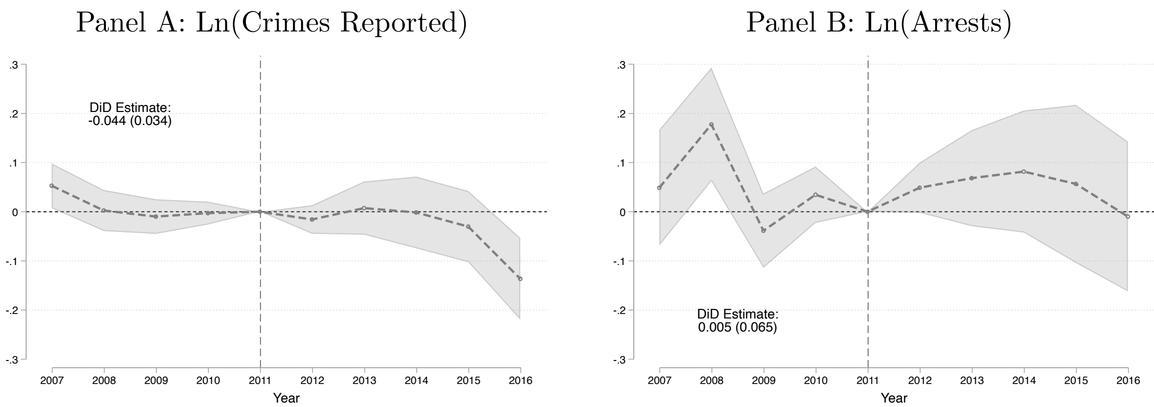



Panel B: Δ Tickets and Crime - Non-CPD




Notes: This figure reports joint distributions of neighborhood-level one-way difference estimates across different outcomes, along with neighborhood-level estimates with pre-reform characteristics. Panels A and B plot the change in sticker tickets for Black and non-Black neighborhoods for CPD and non-CPD agencies, respectively, against neighborhood crime levels. Neighborhood crime is measured as the annual average from 2008-2011. We use levels rather than rates for exposition to account for a handful of commercial neighborhoods with low population, although results using rates are similar. Each point represents a neighborhood, defined at the zip code level. Navy dots represent Black neighborhoods and gray circles represent non-Black neighborhoods. Dashed lines represent linear lines of best fit, estimated separately by neighborhood type.

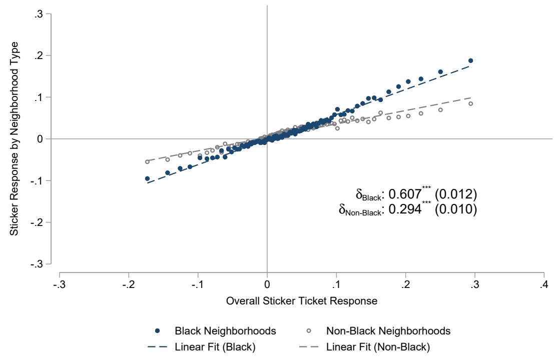
Appendix Figure A9: Event Study Estimates of Crimes Reported to Chicago Police Department and Arrests



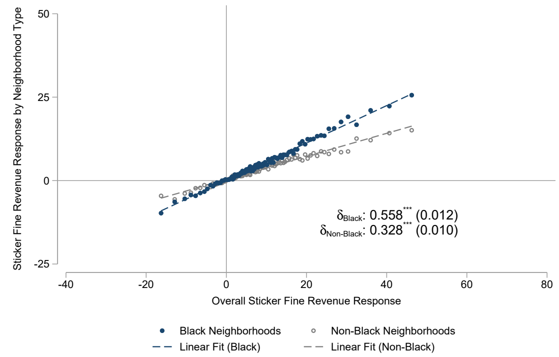

Notes: This figure reports event study estimates of crimes reported to the Chicago Police Department and arrests made for those reported offenses. Each point represents the interaction of $Black_i$ and the corresponding year fixed effect, relative to the level in 2011. Panel A reports results for natural log of crimes reported to the Chicago Police Department and Panel B reports results for the natural log of arrests. Corresponding difference-in-differences estimates are reported in each panel. Shaded regions represent 95 percent confidence intervals with standard errors clustered at the neighborhood level. *** = significant at 1 percent level, ** = significant at 5 percent level, * = significant at 10 percent level.

Appendix Figure A10: Estimating and Decomposing Officer-Specific Responses to Sticker Fine Increase - Empirical Bayes-Adjusted

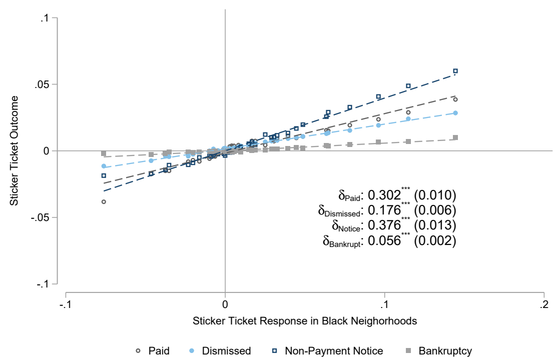
Panel A: P(Sticker | Ticket)



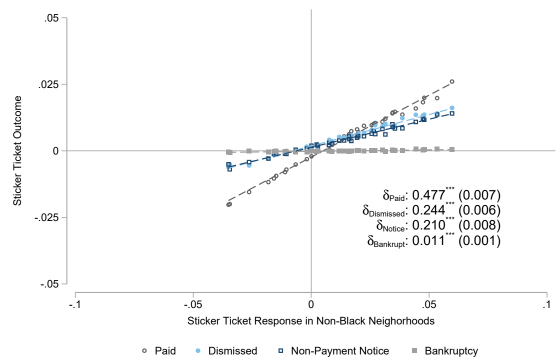

Panel B: E(Revenue | Sticker Ticket)




Panel C: P(· | Sticker Ticket, Black)

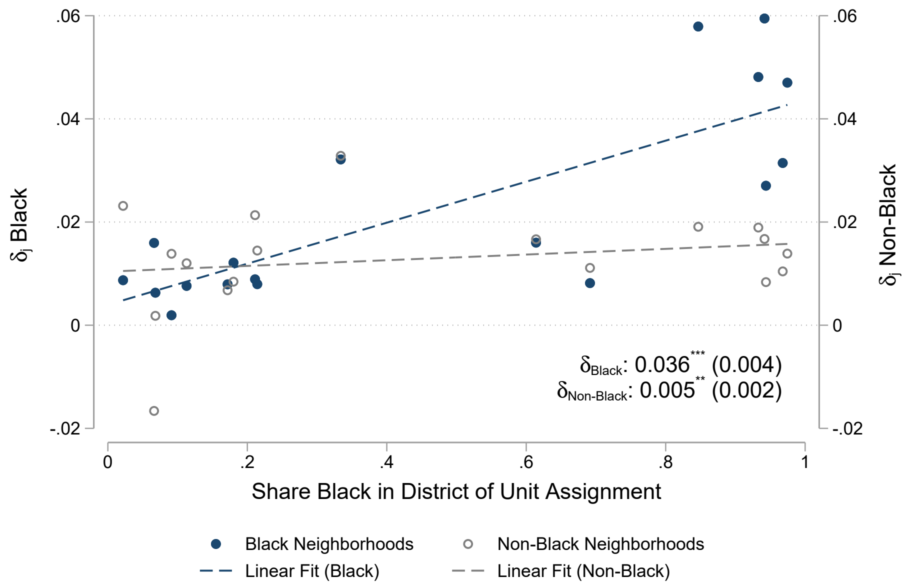



Panel D: P(· | Sticker Ticket, Non-Black)




Notes: This figure plots Empirical Bayes-adjusted estimates of $\delta_j$ for different outcomes against each other. In Panels A and B we plot estimates of neighborhood race-specific $\delta_j$ responses against the overall race-agnostic $\delta_j$ response on the x-axis. In Panels C and D, we plot the race-specific sticker ticket outcomes against the race-specific sticker ticket responses, separately by race. There are 100 bins per outcome in the top two panels and 40 bins per outcome in the lower two panels. For exposition, we drop the first and last bin for each outcome. Reported coefficients estimated on the underlying officer-level estimates. Robust standard errors are reported in parentheses. *** = significant at 1 percent level, ** = significant at 5 percent level, * = significant at 10 percent level.

Appendix Figure A11: Officer-Specific Policy Responses and Assignment Demographics




Notes: This figure reports the correlation between officer-specific $\delta_j$ sticker ticket responses by neighborhood demographic group and the demographic composition of the modal unit assignment. Each point represents a separate unit assignment and plots the within-bin mean against share Black. Blue dots denote $\delta_j(Sticker, Black)$ responses (left axis) and gray circles represent $\delta_j(Sticker, Non-Black)$ responses (right axis). Dashed lines denote linear fits. Reported coefficients and standard errors are estimated on the underlying data. Robust standard errors are reported in parentheses. *** = significant at 1 percent level, ** = significant at 5 percent level, * = significant at 10 percent level.

Appendix Table A1: Annual Volume and Revenue from Top Ten Revenue Generating Tickets in Chicago by Neighborhood Demographic Composition

| | 2007-2011 | | | | | | 2012-2016 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Tickets (000s) | Revenue ($000s) | Avg. Fine | Rev. Share | Rev. Rank | Rev./ E[Rev.] | Tickets (000s) | Revenue ($000s) | Avg. Fine | Rev. Share | Rev. Rank | Rev./ E[Rev.] |
| *Panel A: Black Neighborhoods* | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| No City Sticker | 48 | 5,034 | 120 | 0.24 | 1 | 0.87 | 71 | 8,593 | 200 | 0.33 | 1 | 0.60 |
| Expired Plates | 79 | 3,631 | 50 | 0.18 | 2 | 0.91 | 88 | 4,176 | 60 | 0.16 | 2 | 0.79 |
| Street Cleaning | 34 | 1,816 | 50 | 0.09 | 3 | 1.07 | 33 | 1,901 | 60 | 0.07 | 3 | 0.96 |
| Rear And Front Plate Required | 32 | 1,345 | 50 | 0.06 | 4 | 0.85 | 28 | 991 | 60 | 0.04 | 8 | 0.59 |
| Park In Transit Stand | 13 | 1,239 | 100 | 0.06 | 5 | 0.98 | 12 | 1,123 | 100 | 0.04 | 5 | 0.95 |
| Residential Permit Parking | 18 | 1,076 | 60 | 0.05 | 6 | 0.98 | 15 | 1,047 | 75 | 0.04 | 6 | 0.92 |
| Parking Prohibited Anytime | 15 | 913 | 60 | 0.04 | 7 | 0.99 | 20 | 1,419 | 75 | 0.05 | 4 | 0.96 |
| Within 15' Of Fire Hydrant | 8 | 800 | 100 | 0.04 | 8 | 0.98 | 9 | 1,034 | 150 | 0.04 | 7 | 0.76 |
| Rush Hour Parking | 14 | 796 | 60 | 0.04 | 9 | 0.97 | 9 | 662 | 100 | 0.02 | 10 | 0.77 |
| Expired Meter | 11 | 566 | 50 | 0.03 | 10 | 1.02 | 8 | 426 | 50 | 0.02 | 14 | 1.02 |
| *Panel B: Non-Black Neighborhoods* | | | | | | | | | | | | |
| Expired Meter | 393 | 18,966 | 50 | 0.16 | 1 | 0.97 | 274 | 14,839 | 50 | 0.12 | 3 | 1.08 |
| No City Sticker | 129 | 13,580 | 120 | 0.12 | 2 | 0.88 | 134 | 20,982 | 200 | 0.17 | 1 | 0.78 |
| Expired Plates | 288 | 13,520 | 50 | 0.12 | 3 | 0.94 | 274 | 15,386 | 60 | 0.13 | 2 | 0.94 |
| Street Cleaning | 248 | 13,004 | 50 | 0.11 | 4 | 1.05 | 238 | 13,865 | 60 | 0.12 | 4 | 0.97 |
| Residential Permit Parking | 204 | 11,782 | 60 | 0.10 | 5 | 0.96 | 164 | 11,986 | 75 | 0.10 | 5 | 0.97 |
| Parking Prohibited Anytime | 129 | 7,133 | 60 | 0.06 | 6 | 0.92 | 109 | 7,851 | 75 | 0.07 | 6 | 0.96 |
| Rush Hour Parking | 108 | 6,327 | 60 | 0.05 | 7 | 0.98 | 59 | 4,871 | 100 | 0.04 | 8 | 0.83 |
| Rear And Front Plate Required | 122 | 5,437 | 50 | 0.05 | 8 | 0.89 | 89 | 3,631 | 60 | 0.03 | 10 | 0.68 |
| Within 15' Of Fire Hydrant | 38 | 3,749 | 100 | 0.03 | 9 | 0.99 | 34 | 4,085 | 150 | 0.03 | 9 | 0.81 |
| Park In Transit Stand | 39 | 3,667 | 100 | 0.03 | 10 | 0.94 | 26 | 2,465 | 100 | 0.02 | 11 | 0.95 |

Notes: This table reports average annual characteristics of the top ten revenue generating tickets from 2007-2011 and characteristics for the same set of tickets from 2012-2016, separately by neighborhood demographic composition. Panel A reports statistics for Black neighborhoods, define as neighborhoods whose population is at least seventy-five percent Black, and Panel B reports statistics for Non-Black neighborhoods. The type of ticket is listed in each row. Columns 1 and 7 report annual ticket volume, Columns 2 and 8 report annual ticket revenue, Columns 3 and 9 report the modal fine amount, Columns 4 and 10 report the revenue share of the listed ticket, along with the revenue share rank in Columns 5 and 11. Columns 6 and 12 report the ratio of revenue received and expected revenue, calculated as the base fine amount times ticket volume. The revenue share is less than one when collected revenue plus applicable late fees is less than the expected collected amount if all written tickets were paid on time, and is greater than one if collected revenue plus applicable late fees exceeds this expectation.

Appendix Table A2: Robustness Checks of Ticket-Level Regressions

| | Sticker | | | | | Non-sticker | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| *Panel A: CPD* | | | | | | | | | | |
| Tickets | 0.021** | 0.038*** | 0.038*** | 0.045*** | 0.037*** | -0.021** | -0.038*** | -0.038*** | -0.045*** | -0.037*** |
| | (0.009) | (0.007) | (0.007) | (0.006) | (0.007) | (0.009) | (0.007) | (0.007) | (0.006) | (0.007) |
| Revenue | -24.371*** | -27.297*** | -27.189*** | -29.100*** | -24.127*** | -10.500*** | -9.989*** | -9.952*** | -10.041*** | -9.367*** |
| | (4.204) | (3.709) | (3.918) | (4.063) | (4.002) | (1.043) | (1.014) | (1.013) | (0.905) | (1.080) |
| Paid | -0.052*** | -0.082*** | -0.081*** | -0.097*** | -0.072*** | -0.054*** | -0.066*** | -0.063*** | -0.068*** | -0.059*** |
| | (0.013) | (0.011) | (0.011) | (0.010) | (0.012) | (0.010) | (0.008) | (0.007) | (0.007) | (0.007) |
| Notice | 0.026** | 0.062*** | 0.065*** | 0.068*** | 0.056*** | 0.034*** | 0.048*** | 0.047*** | 0.048*** | 0.046*** |
| | (0.012) | (0.011) | (0.009) | (0.013) | (0.011) | (0.007) | (0.005) | (0.004) | (0.004) | (0.005) |
| Bankruptcy | 0.009*** | 0.015*** | 0.015*** | 0.017*** | 0.013*** | 0.009*** | 0.011*** | 0.011*** | 0.011*** | 0.010*** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Dismissed | 0.017** | 0.005 | 0.001 | 0.012 | 0.002 | 0.011* | 0.007 | 0.005 | 0.009** | 0.004 |
| | (0.007) | (0.008) | (0.004) | (0.009) | (0.008) | (0.006) | (0.005) | (0.004) | (0.005) | (0.004) |
| *Panel B: Non-CPD* | | | | | | | | | | |
| Tickets | 0.010 | 0.011** | 0.014*** | 0.007* | 0.015*** | -0.010 | -0.011** | -0.014*** | -0.007* | -0.015*** |
| | (0.006) | (0.005) | (0.005) | (0.004) | (0.003) | (0.006) | (0.005) | (0.005) | (0.004) | (0.003) |
| Revenue | -29.991*** | -30.451*** | -27.937*** | -29.178*** | -30.664*** | -4.068*** | -3.611*** | -3.044*** | -3.133*** | -4.095*** |
| | (3.120) | (2.919) | (2.599) | (3.072) | (2.990) | (0.907) | (0.821) | (0.683) | (0.653) | (0.773) |
| Paid | -0.123*** | -0.121*** | -0.111*** | -0.121*** | -0.123*** | -0.026** | -0.038*** | -0.034*** | -0.025*** | -0.045*** |
| | (0.010) | (0.010) | (0.009) | (0.009) | (0.009) | (0.011) | (0.008) | (0.007) | (0.007) | (0.005) |
| Notice | 0.071*** | 0.071*** | 0.075*** | 0.069*** | 0.073*** | 0.017** | 0.022*** | 0.023*** | 0.017*** | 0.026*** |
| | (0.008) | (0.006) | (0.006) | (0.007) | (0.006) | (0.007) | (0.005) | (0.005) | (0.004) | (0.003) |
| Bankruptcy | 0.019*** | 0.020*** | 0.020*** | 0.017*** | 0.020*** | 0.004*** | 0.005*** | 0.005*** | 0.003*** | 0.005*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Dismissed | 0.033*** | 0.030*** | 0.016*** | 0.035*** | 0.030*** | 0.006 | 0.011* | 0.005 | 0.005 | 0.013** |
| | (0.008) | (0.007) | (0.004) | (0.007) | (0.007) | (0.006) | (0.005) | (0.004) | (0.004) | (0.006) |
| Zip Fixed Effects | No | Yes | Yes | Yes | Yes | No | Yes | Yes | Yes | Yes |
| Year Fixed Effects | No | Yes | Yes | Yes | Yes | No | Yes | Yes | Yes | Yes |
| Owner Controls | No | No | Yes | No | No | No | No | Yes | No | No |
| Black Majority Cutoff | 0.75 | 0.75 | 0.75 | 0.50 | 0.90 | 0.75 | 0.75 | 0.75 | 0.50 | 0.90 |

Notes: This table reports robustness checks of our ticket-level difference-in-differences (DiD) estimates. Panel A reports results for CPD-written tickets and Panel B reports results for non-CPD-written tickets. The outcome is listed in each row. Columns 1-5 report estimates for sticker tickets and Columns 6-10 report estimates for non-sticker tickets. Each cell corresponds to a different point estimate. Column 1 estimates the simple DiD without any additional fixed effects, Column 2 reproduces our main text estimate, Column 3 includes controls for owner city, car make, and an indicator for out of state license place, Column 4 redefines majority Black to be neighborhoods with above 50 percent Black population share, and Column 5 changes the same threshold to 90 percent. Columns 6-10 repeat the analogous exercises. Standard errors clustered at the zip code level are reported in parentheses. *** = significant at 1 percent level, ** = significant at 5 percent level, * = significant at 10 percent level.

Appendix Table A3: Robustness Checks of Neighborhood-Level Regressions

| | Sticker | | | | Non-sticker | | | |
|---|---|---|---|---|---|---|---|---|
| *Panel A: CPD* | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Tickets | 2,490*** | 2,490*** | 2,166*** | 2,347*** | 11,936*** | 11,936*** | 11,729*** | 11,287*** |
| | (461) | (464) | (385) | (508) | (1,485) | (1,494) | (1,496) | (1,532) |
| Revenue | 271,341*** | 271,341*** | 249,193*** | 260,740*** | 576,982*** | 576,982*** | 557,857*** | 548,624*** |
| | (50,779) | (51,102) | (42,036) | (56,236) | (77,756) | (78,250) | (78,628) | (81,178) |
| Paid | 363*** | 363*** | 355*** | 336*** | 6,593*** | 6,593*** | 6,803*** | 6,292*** |
| | (113) | (114) | (100) | (122) | (898) | (903) | (951) | (912) |
| Notice | 1,316*** | 1,316*** | 1,088*** | 1,249*** | 2,315*** | 2,315*** | 1,979*** | 2,180*** |
| | (220) | (222) | (189) | (244) | (306) | (308) | (276) | (334) |
| Bankruptcy | 236*** | 236*** | 195*** | 222*** | 353*** | 353*** | 287*** | 325*** |
| | (38) | (38) | (33) | (42) | (54) | (54) | (47) | (58) |
| Dismissed | 574*** | 574*** | 528*** | 539*** | 2,674*** | 2,674*** | 2,659*** | 2,489*** |
| | (107) | (108) | (87) | (117) | (352) | (355) | (356) | (353) |
| *Panel B: Non-CPD* | | | | | | | | |
| Tickets | -294*** | -294*** | -323*** | -314*** | -3,188** | -3,188** | -3,432** | -3,546** |
| | (82) | (83) | (78) | (85) | (1,393) | (1,402) | (1,484) | (1,369) |
| Revenue | -77,131*** | -77,131*** | -80,922*** | -80,994*** | -321,747*** | -321,747*** | -339,299*** | -348,330*** |
| | (17,194) | (17,303) | (17,588) | (17,189) | (76,874) | (77,362) | (79,655) | (73,093) |
| Paid | -374*** | -374*** | -371*** | -383*** | -2,376** | -2,376** | -2,522** | -2,642** |
| | (64) | (65) | (58) | (68) | (1,112) | (1,119) | (1,185) | (1,096) |
| Notice | 58* | 58* | 40 | 53 | -159 | -159 | -165 | -189 |
| | (34) | (34) | (26) | (37) | (128) | (129) | (128) | (131) |
| Bankruptcy | 29*** | 29*** | 23*** | 28*** | -7 | -7 | -14 | -14 |
| | (7) | (7) | (6) | (8) | (17) | (17) | (14) | (18) |
| Dismissed | -9 | -9 | -14 | -12 | -646*** | -646*** | -731*** | -702*** |
| | (20) | (20) | (18) | (21) | (188) | (189) | (206) | (181) |
| Zip Fixed Effects | No | Yes | Yes | Yes | No | Yes | Yes | Yes |
| Year Fixed Effects | No | Yes | Yes | Yes | No | Yes | Yes | Yes |
| Owner Controls | No | No | No | No | No | No | No | No |
| Black Majority Cutoff | 0.75 | 0.75 | 0.50 | 0.90 | 0.75 | 0.75 | 0.50 | 0.90 |

Notes: This table reports robustness checks of our neighborhood difference-in-differences (DiD) estimates. Panel A reports results for CPD-written tickets and Panel B reports results for non-CPD-written tickets. The outcome is listed in each row. Columns 1-4 report estimates for sticker tickets and Columns 5-8 report estimates for non-sticker tickets. Each cell corresponds to a different point estimate. Column 1 estimates the simple DiD without any additional fixed effects, Column 2 reproduces our main text estimate, Column 3 redefines majority Black to be neighborhoods with above 50 percent Black population share, and Column 4 changes the same threshold to 90 percent. Columns 5-8 repeat the analogous exercises. Standard errors clustered at the zip code level are reported in parentheses. *** = significant at 1 percent level, ** = significant at 5 percent level, * = significant at 10 percent level.

Appendix Table A4: Difference-in-Differences Estimates of Disparate Ticketing and Ticket Outcomes at Census Tract-Level

| | Tickets | Revenue | Paid | Notice | Bankruptcy | Dismissed |
|---|---|---|---|---|---|---|
| *Ticket-Level Estimates* | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A: CPD* | | | | | | |
| Sticker: | 0.046*** | -32.450*** | -0.100*** | 0.076*** | 0.020*** | 0.004 |
| | (0.003) | (1.476) | (0.005) | (0.004) | (0.002) | (0.004) |
| Non-Sticker: | -0.046*** | -10.681*** | -0.071*** | 0.051*** | 0.012*** | 0.009*** |
| | (0.003) | (0.542) | (0.004) | (0.002) | (0.001) | (0.003) |
| *Panel B: Non-CPD* | | | | | | |
| Sticker: | 0.013*** | -32.823*** | -0.136*** | 0.078*** | 0.019*** | 0.039*** |
| | (0.002) | (1.521) | (0.005) | (0.004) | (0.002) | (0.004) |
| Non-Sticker: | -0.013*** | -4.416*** | -0.042*** | 0.024*** | 0.005*** | 0.012*** |
| | (0.002) | (0.341) | (0.003) | (0.002) | (0.001) | (0.003) |
| *Neighborhood-Level Estimates* | | | | | | |
| *Panel C: CPD* | | | | | | |
| Sticker: | 157*** | 16,453*** | 29*** | 77*** | 14*** | 37*** |
| | (11) | (1,108) | (3) | (5) | (1) | (3) |
| Non-Sticker: | 922*** | 42,558*** | 548*** | 149*** | 21*** | 205*** |
| | (106) | (5,445) | (69) | (10) | (2) | (30) |
| *Panel D: Non-CPD* | | | | | | |
| Sticker: | -25*** | -8,078*** | -25*** | 1 | 1*** | -2** |
| | (3) | (616) | (2) | (1) | (0) | (1) |
| Non-Sticker: | -220*** | -26,492*** | -157*** | -9 | -1** | -52*** |
| | (68) | (4,703) | (50) | (6) | (1) | (12) |

Notes: This table reports difference-in-differences estimates of the change in ticketing behavior across neighborhoods by ticket type and ticketing agency, estimated at the ticket level in Panels A and B and estimated at the tract level in Panels C and D. Each coefficient is from a separate regression and represents the interaction of $Black \times Post$. Panels A and C report results for tickets written by the Chicago Police Department. Panels B and D reports results for tickets written by the Parking Enforcement Authority (Non-CPD). Rows labeled as Sticker report results for sticker tickets and rows labeled as Non-Sticker report results for all other tickets. Column 1 reports the probability a ticket is a sticker or non-sticker ticket or the number of each ticket type in the area-level estimates. Column 2 reports the associated collected revenue, Columns 3-6 report the outcomes of the tickets as paid, received a non-payment notice, bankrupt, or dismissed. All regressions include tract and year fixed effects. Standard errors clustered at the tract level are reported in parentheses. *** = significant at 1 percent level, ** = significant at 5 percent level, * = significant at 10 percent level.

Appendix Table A5: Decomposing Differential Outcomes by Owner Zip Code Demographics

| | Tickets | Revenue | Paid | Notice | Bankruptcy | Dismissed |
|---|---|---|---|---|---|---|
| *Ticket-Level Estimates* | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A: CPD* | | | | | | |
| Main: | 0.038*** | -27.297*** | -0.082*** | 0.062*** | 0.015*** | 0.005 |
| | (0.007) | (3.709) | (0.011) | (0.011) | (0.003) | (0.008) |
| Black Zip Owner: | -0.021*** | 4.482** | -0.121*** | 0.066*** | 0.019*** | 0.016*** |
| | (0.006) | (1.788) | (0.007) | (0.008) | (0.002) | (0.002) |
| Non-Black Zip Owner: | 0.007 | -29.569*** | 0.027*** | -0.003 | -0.003 | -0.014*** |
| | (0.007) | (3.087) | (0.008) | (0.007) | (0.002) | (0.003) |
| *Panel B: Non-CPD* | | | | | | |
| Main: | 0.011** | -30.451*** | -0.121*** | 0.071*** | 0.020*** | 0.030*** |
| | (0.005) | (2.919) | (0.010) | (0.006) | (0.002) | (0.007) |
| Black Zip Owner: | -0.004 | 23.710*** | -0.096*** | 0.069*** | 0.018*** | 0.006*** |
| | (0.005) | (2.190) | (0.004) | (0.005) | (0.002) | (0.002) |
| Non-Black Zip Owner: | 0.004 | -46.788*** | -0.021*** | 0.015*** | 0.004*** | 0.006** |
| | (0.007) | (2.430) | (0.007) | (0.004) | (0.002) | (0.003) |
| *Neighborhood-Level Estimates* | | | | | | |
| *Panel C: CPD* | | | | | | |
| Main: | 2,490*** | 271,341*** | 363*** | 1,316*** | 236*** | 574*** |
| | (464) | (51,102) | (114) | (222) | (38) | (108) |
| Black Zip Owner: | 1,464*** | 196,497*** | 53 | 968*** | 184*** | 257*** |
| | (278) | (32,861) | (66) | (151) | (25) | (43) |
| Non-Black Zip Owner: | 772*** | 65,194*** | 269*** | 323*** | 48*** | 132*** |
| | (179) | (21,376) | (57) | (85) | (15) | (36) |
| *Panel D: Non-CPD* | | | | | | |
| Main: | -294*** | -77,131*** | -374*** | 58* | 29*** | -9 |
| | (83) | (17,303) | (65) | (34) | (7) | (20) |
| Black Zip Owner: | -83* | 25,558*** | -183*** | 75*** | 24*** | 1 |
| | (46) | (7,683) | (41) | (24) | (5) | (7) |
| Non-Black Zip Owner: | -212*** | -96,605*** | -175*** | -15 | 5* | -27*** |
| | (46) | (12,785) | (31) | (13) | (3) | (10) |

Notes: This table decomposes our main difference-in-differences estimates into outcomes experienced by owners in majority (>75 percent) Black neighborhoods and those in non-Black majority neighborhoods. We interact each outcome in the column title with indicators for $Black_i$ and $(1 - Black_i)$. The “Main” row reproduces our main text estimate and the corresponding “Black” and “Non-Black” rows decompose the Main outcome following the previous description. Due to missing owner information for some tickets, the decomposition will not exactly add to the full sample estimate. Panels A and C report results for CPD-written tickets and Panels B and D report results for non-CPD-written tickets. The upper panels report ticket-level estimates and the lower panels report neighborhood-level estimates. Standard errors clustered at the zip code level are reported in parentheses. *** = significant at 1 percent level, ** = significant at 5 percent level, * = significant at 10 percent level.

Appendix Table A6: Testing Departmental Responses to Alternative Treatment Margins

| | Sticker Tickets | | | | | |
|---|---|---|---|---|---|---|
| *Panel A: CPD* | (1) | (2) | (3) | (4) | (5) | (6) |
| Black × Post | 2,490*** | | | | | 1,129 |
| | (464) | | | | | (720) |
| High Income × Post | | -689** | | | | -328 |
| | | (268) | | | | (281) |
| High Crime × Post | | | 2,005*** | | | 1,206** |
| | | | (426) | | | (523) |
| High Sticker Ticket Rate × Post | | | | 1,755*** | | 691* |
| | | | | (460) | | (369) |
| High Sticker Ticket Payment Rate × Post | | | | | -863*** | 30 |
| | | | | | (275) | (268) |
| *Panel B: Non-CPD* | | | | | | |
| Black × Post | -294*** | | | | | -40 |
| | (83) | | | | | (211) |
| High Income × Post | | 80 | | | | 139 |
| | | (117) | | | | (125) |
| High Crime × Post | | | -256*** | | | -229 |
| | | | (76) | | | (141) |
| High Sticker Ticket Rate × Post | | | | -260*** | | -175 |
| | | | | (75) | | (115) |
| High Sticker Ticket Payment Rate × Post | | | | | -11 | -189* |
| | | | | | (106) | (101) |

Notes: This table presents difference-in-differences estimates using alternative treatment definitions. Panel A reports results for CPD-written tickets, and Panel B reports results for non-CPD-written tickets. The corresponding interaction is listed in each row. The outcome in all columns is the number of sticker tickets. Non-Black alternative treatment definitions are defined as being in the upper quartile or not. All regressions include zip code and year fixed effects. Standard errors clustered at the zip code level are reported in parentheses. *** = significant at 1 percent level, ** = significant at 5 percent level, * = significant at 10 percent level.

Appendix Table A7: Decomposing Differential Outcomes by Non-Race Neighborhood Characteristics Within Black Neighborhoods

| | Income | | Crime Rate | | Sticker Ticket Rate | | Sticker Ticket Payment Rate | |
|---|---|---|---|---|---|---|---|---|
| | High | Low | High | Low | High | Low | High | Low |
| *Panel A: CPD* | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Sticker | 3,055*** | 1,925*** | 3,017*** | 1,964*** | 2,592*** | 1,323*** | 1,206*** | 2,516*** |
| | (537) | (630) | (463) | (699) | (476) | (276) | (284) | (450) |
| *p*-value | 0.164 | | 0.200 | | 0.000 | | 0.000 | |
| *Panel B: Non-CPD* | | | | | | | | |
| Sticker | -338*** | -251** | -328*** | -261** | -373*** | -242*** | -4 | -397*** |
| | (106) | (99) | (75) | (126) | (137) | (70) | (87) | (100) |
| *p*-value | 0.489 | | 0.600 | | 0.336 | | 0.005 | |

Notes: This table reports difference-in-differences results which decompose the differential response in Black neighborhoods along other non-race characteristics, estimated at the neighborhood-level. Each non-race characteristic is defined in the pre-reform period and splits the subsample of Black neighborhoods into above- and below-median groups based on the statistic listed in the column title. Sticker ticket rate is the fraction of neighborhood tickets which are sticker tickets. Sticker ticket payment rate is the fraction of neighborhood sticker tickets which are paid. Panel A reports results for CPD-written tickets and Panel B reports results for non-CPD-written tickets. Listed p-values test for differences between coefficient estimates in Black neighborhoods. All regressions include zip code and year fixed effects. Standard errors clustered at the zip code level are reported in parentheses. *** = significant at 1 percent level, ** = significant at 5 percent level, * = significant at 10 percent level.

Appendix Table A8: Correlating Officer Policy Responses with Observable Characteristics - All Officers

| | $\delta_j$ Response | | | |
|---|---|---|---|---|
| *Panel A: $\delta_j$ (Sticker, Black)* | (1) | (2) | (3) | (4) |
| Male | 0.001 | | | 0.001 |
| | (0.003) | | | (0.003) |
| Age | -0.000** | | | -0.000 |
| | (0.000) | | | (0.000) |
| Hispanic | | -0.001 | | -0.001 |
| | | (0.003) | | (0.003) |
| Asian or Native American | | -0.002 | | -0.003 |
| | | (0.006) | | (0.006) |
| Black | | -0.008** | | -0.007* |
| | | (0.004) | | (0.004) |
| Years Experience | | | -0.000** | -0.000 |
| | | | (0.000) | (0.000) |
| Complaints per Year | | | 0.000 | -0.000 |
| | | | (0.002) | (0.002) |
| Tickets Issued per Year(00s) | | | 0.001* | 0.001 |
| | | | (0.001) | (0.001) |
| *Panel B: $\delta_j$ (Sticker, Non-Black)* | | | | |
| Male | -0.000 | | | -0.001 |
| | (0.002) | | | (0.002) |
| Age | -0.000 | | | -0.000 |
| | (0.000) | | | (0.000) |
| Hispanic | | 0.001 | | 0.001 |
| | | (0.002) | | (0.002) |
| Asian or Native American | | 0.005 | | 0.005 |
| | | (0.005) | | (0.005) |
| Black | | 0.000 | | 0.001 |
| | | (0.002) | | (0.002) |
| Years Experience | | | 0.000 | 0.000 |
| | | | (0.000) | (0.000) |
| Complaints per Year | | | 0.001 | 0.001 |
| | | | (0.001) | (0.001) |
| Tickets Issued per Year(00s) | | | 0.001 | 0.001 |
| | | | (0.001) | (0.001) |
| Observations | 6,153 | 6,153 | 6,153 | 6,153 |
| Unit Fixed Effects | Yes | Yes | Yes | Yes |

Notes: This table reports regressions of officer-specific $\delta_j$ responses against officer-level observables. The sample includes all police officers. The dependent variable in Panel A is the officer-specific $\delta_j$ for sticker tickets in Black neighborhoods and the dependent variable in Panel B is the corresponding $\delta_j$ for sticker tickets in Non-Black neighborhoods. Experience, complaints and tickets issued per year are all measured prior to the policy change. Robust standard errors are reported in parentheses. *** = significant at 1 percent level, ** = significant at 5 percent level, * = significant at 10 percent level.

## Appendix B: Model of Officer Behavior

In this section, we present a simple model of CPD and non-CPD officer behavior to provide a simple microfoundation for understanding the differences between officers across departments and illustrating how the reform impacts various channels which influence officer behavior.

*Non-CPD Behavior:* We operationalize non-CPD agencies as maximizing ticket volume:

$$\max_{s_n} \; s_n v_n - \underbrace{c(s_n)}_{\substack{\text{Search}\\\text{cost}}}$$

where $s_n$ is a search in neighborhood $n$, $v_n$ is the violation rate in neighborhood $n$, and $c(s_n) = c_n s_n^2/2$ is the neighborhood-specific convex search cost. Standard first order conditions equate the violation rate with the marginal cost of search. Notably, this solution is independent of the expected value of the ticket, including both the fine amount and payment probability.

*CPD Behavior:* In contrast, CPD maximizes revenue and other objectives:

$$\max_{s_n} \; s_n(\underbrace{f * p_n * v_n}_{\text{E[Revenue]}}) - \underbrace{c(s_n)}_{\substack{\text{Search}\\\text{cost}}}$$

In this setup $E$[Revenue]$= (f * p_n * v_n)$, where $f$ is the fine, $p_n$ is the probability a ticket gets paid and $c(s_n) = c_n s_n^2/2$ is the cost of search, including the opportunity cost.

The first order conditions of this problem should equate marginal expected revenue to marginal costs. Thus, there will more tickets in neighborhood $n$ if, all else equal there are higher violation rates, higher payment rates, or lower marginal costs. The fine increase will affect both the level and distribution of tickets. Writing out the FOCs:

$$\underbrace{f * p_n * v_n}_{\substack{\text{Marginal}\\\text{revenue}}} = \underbrace{c_n s_n^*}_{\substack{\text{Marginal}\\\text{cost}}}$$

We are interested in the change in search with respect to a change in fine, $\frac{\delta s_n^*}{\delta f}$, implying:

$$\underbrace{p_n * v_n}_{\substack{\text{Revenue}\\\text{effect}}} + \underbrace{f * \frac{\delta p_n}{\delta f} * v_n}_{\substack{\text{Payment rate}\\\text{effect}}} + \underbrace{f * p_n * \frac{\delta v_n}{\delta f}}_{\substack{\text{Deterrence}\\\text{effect}}} = c_n \frac{\delta s_n^*}{\delta f}$$

The first term of this equation $(p_n * v_n)$ can be thought of as a revenue effect, which we find as smaller in Black neighborhoods. The second term, the payment rate effect, is likely smaller in Black neighborhoods because of a larger reduction in repayment, with low violation rates across all neighborhoods. The final term, we can label a deterrence effect, which we find is relatively small. We conclude that the the larger increase in tickets in Black neighborhoods is likely due to smaller marginal costs for CPD officers.