Disparate Fine Collection: Evidence using Chicago Parking Tickets

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Abstract

Using a plausibly exogenous increase in the fine for failing to purchase annual vehicle registration in 2012, colloquially known as the sticker tax, I test if Chicago police disparately enforced parking compliance across black and non-black neighborhoods from 2007 to 2017. I find that police behavior is responsive to the penalty structure of the fine and are 20 to 50 percent more likely to apply the sticker fine to black neighborhoods after the increase. This disparate enforcement is robust to employment controls and is not driven by changing compliance rates across neighborhoods. In contrast, I find that parking enforcement agents do not disparately enforce the tickets across black and non-black neighborhoods. I attribute this difference in behavior between parking enforcement agents and police officers to the lack of work evaluations based on ticketing productivity for police officers. Since police officers are not evaluated by their parking citation productivity, they do not behave as revenue-maximizing agents in the context of parking enforcement.

1 Introduction

Parking fines are one of the major revenue generators for cities in the United States. For example, Chicago raised \$264 million in 2017, which was equivalent to an annual \$97.20 per-capita tax (Diskin, 2019). Importantly, the ability of the city to raise its revenue from these types of fines depends on its enforcement agents and the policies it has in place. Therefore, if the agents disparately apply the tickets, this may disproportionately tax a subset of the population, while inefficiently raising revenue.

In this paper, I test whether police officers disparately enforce parking fines on black residents in Chicago. I exploit the 2012 parking fine increase for not displaying the required city sticker, colloquially known as the 'sticker tax,' as a plausibly exogenous shock on the distribution of parking tickets across neighborhoods.[1] In October 2011, the city announced it would increase the fine for sticker non-compliance by 67 percent, from \$120 to \$200, for passenger vehicles (Federation, 2012). The stated goal of the tax was to increase compliance rates for vehicle registration. The increased fine was passed in order to help raise revenue to close the projected \$637 million deficit in the city's budget in 2012.

Using administrative parking ticket data from 2007 to 2017 in Chicago, I use an event study framework to examine the differential change in policing behavior across black and non-black neighborhoods. I use the proportion of black residents within each community area as a proxy for whether the neighborhood is considered black or non-black. After controlling for vehicle characteristics, the interaction between whether the community area is predominantly black in 2011 and year dummies will describe the differential change in police behavior as a result of the fee increase. This estimation strategy is well-suited for Chicago since its neighborhoods are highly segregated between black and white residents.

My main result shows that police officers were responsive to the changing penalty

[1] To be clear, motor vehicle owners in Chicago are required to register their vehicle with the state and with the city and the sticker tax refers to registration within the city.

structure of the fine. Specifically, police officers were 20 to 50 percent even more likely to give the sticker fine to black neighborhoods compared to non-black neighborhoods after the fine increase, which I interpret as evidence of disparate policing. This disproportionate sticker application was equivalent to a \$7 to \$19 increase in the per-capita tax for parking for black neighborhoods, which was \$26 in 2011. Whereas for non-black neighborhoods, it was equivalent to a \$4 to \$7 increase, which was \$38 in 2011.

To ensure that my findings are not driven by changing compliance rates, I also test if sticker purchasing behavior across black and non-black neighborhoods changed during this time. I find no significant difference in the total sticker purchases between black and non-black neighborhoods. Furthermore, I find that the average revenue from sticker purchases for black neighborhoods increased by approximately \$21,000 more than non-black neighborhoods, even when controlling for population changes. In per-capita terms, this is equivalent to a \$0.46 to \$4.26 increase in the annual registration tax.

Lastly, I hypothesize that incentivizing revenue generating behavior through work evaluations based on parking citation productivity may reduce disparate treatment. Because police officers are not evaluated based on their parking enforcement, they may rely on their own preferences rather than that of the budget maximizing principals when determining their ticket productivity. I test this by comparing the ticketing behavior of Chicago police to parking enforcement agents. One major distinction between these two types of agents is that parking enforcement agents can only give non-moving violations while police officers' have other responsibilities and thus may not necessarily be as concerned with their parking ticket productivity.[2] I show that only Chicago police significantly change their sticker ticketing behavior across black and non-black neighborhoods after the fine increases whereas parking enforcement agents do not. I interpret this as suggestive evidence in support of my hypothesis.

This research relates to the existent literature examining law enforcement agents' role

[2]The primary function of Chicago Police is to "work for the benefit of its citizens by protecting life and property from harm and maintain order." See https://www.chicago.gov/content/dam/city/depts/dhr/supp_info/JobSpecifications/PublicSafetyServices/9100_PoliceGeneralDutySeries/9161_POLICE_OFFICER.pdf for details.

in contributing to city revenue. One possible explanation for my results showing that police officers do not behave as agents of revenue-maximizing principals in the context of parking enforcement is along the lines of a political economy story suggested by Makowsky and Stratmann (2009). In their paper, they find that police officers take into consideration the driver's voting status and the municipal budget when determining whether to give speeding tickets. Both out-of-town or out-of-state drivers and the fiscal status of the municipality are positively correlated to the probability of the police officer giving a speed citation. Thus, police officers target drivers least likely to protest the speeding citation and are more likely to pay the full citation amount, thereby increasing city revenue.

In contrast to their results, I focus on the disparate enforcement of the sticker citation, which do not apply to out-of-city drivers or out-of-state drivers. Thus, the ability to target certain citations based on drivers most likely to pay the full amount is not possible in this context. Furthermore, parking enforcement has even lower returns to public safety and given the presence of parking enforcement agents, police officers may be even less motivated to base their parking citation decisions based on revenue-maximizing behavior. Additionally, my findings that only police officers disparately enforce parking citations supports Makowsky and Stratmann (2009) hypothesis that explicit work evaluations based on ticket productivity influence whether law enforcement agents behave more as revenue-maximizing agents.

Second, my study contributes to the growing literature on disparate policing in the context of motorists and law enforcement. Many earlier contributions to the literature have linked this disparate policing to racial bias (Anbarci and Lee, 2014; Arnold et al., 2018; Goncalves and Mello, 2017; Luh, 2019; Persico and Todd, 2005; Shayo and Zussman, 2011). However, these papers rely on observing direct interactions between the law enforcement agent and the affected individuals. Thus, interactions that the law enforcement officer chooses not to initiate with the motorist will be unobserved in the data, which may reduce estimates of bias (Knox et al., 2019).

With parking tickets, the police officer generally does not need to directly interact with the motorist to issue the ticket and guilt is already determined by characteristics of the vehicle and how the vehicle is parked. Since the motorist may be unobserved, characteristics of the neighborhood, such as racial makeup, may have more influence on police officer's parking enforcement behavior and thereby the disparate enforcement, rather than characteristics of the motorist. Further, the increased per-capita tax as a result of disparate enforcement of sticker citations provide slight evidence of spillover effects onto residents of black neighborhoods. In addition, I also provide a new policing context in which racial bias may be present.

The rest of my paper is outlined as follows. In Section II, I describe the background of the fine increase along with descriptive information of Chicago's parking system. In Section III, I describe my data sources. Section IV details my estimation strategy and empirical results. I conclude in Section V.

2 Background

2.1 Chicago Parking

The city of Chicago relies heavily on parking ticket revenue, with 7 percent of its 3.6 billion dollar operating budget coming from the fines it collects.[3] Each year, the city issues over 3 million tickets for parking violations, vehicle compliance, and automated traffic camera violations (Sanchez and Kambhampati, 2018). One major, unique feature of Chicago parking is that the fine has no statute of limitations, which means that the unpaid amount can follow the driver for his entire lifetime.[4]

Chicago's parking fine is particularly punitive for a variety of reasons. If the fine is unpaid for a certain amount of time, the fine ends up doubling. 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

[3]Compared to Los Angeles where parking fine revenue is only 5 percent of the budget

[4]Compared to Los Angeles again where the statue of limitations is only 5-Years or New York City where the statute of limitations is 8 years.

past due, the car can be impounded or booted and the vehicle owner receives a seizure notice. If after ten or more non-moving violations (parking tickets) or five unpaid tickets from automated red-light or speed cameras, the city of Chicago will suspend the vehicle owner's drivers' license. Drivers who owe a high amount of fines can choose to enter into a payment plan with the city. But, the payment plan is not designed for ticket holders with high fees. To qualify for the standard payment plan, the driver must pay a $1000 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 which 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.

Column (1) of Table 1 show the top seven most given parking tickets from 2007 to 2011. The most given ticket has a fine of $60. Out of the top tickets, only three are related to parking quality or parking permissions (residential permit parking, expired meter, parking in prohibited areas). Four of the most popular tickets are related to having correct licensing or registration. Notably, the fourth most common ticket, which requires having a city sticker, has a disproportionately high fine of $125, which is almost double the next most expensive ticket of $75 in Table 1.

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 relatively cheap at only $75 for sedans and $120 for larger passenger vehicles, the fine for failing to buy the sticker or failing to display the sticker was $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 (Federation, 2012).[5] Further, the fine for not paying the tax would increase from \$120 to \$200. The registration cost and the fine increase was ostensibly motivated by a need to pay for fixing Chicago streets. The increases were announced in October 2011 to be enacted in January 2012.

This fee was announced in conjunction with other aggressive revenue-generating policies in an attempt to close a \$637 million dollar 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. Specifically, 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 (Ruthhart and Reporter, 2014). For city employees, the mayor announced additional punishments for scofflaw. For exmaple, 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 (PEA) can give out parking citations in neighborhoods. PEAs are allowed to enforce non-moving ordinances in Chicago and are often hired through a firm contracted with the city to enforce parking, rather than directly by the city. In order to increase efficiency and maximize revenue, PEAs are oftentimes evaluated based on their ticketing productivity and are sometimes promoted based on their tickets per shift.[6]

On the other hand, Chicago police officers's main job is not parking enforcement and their parking ticket productivity is not as important. In recent years, Chicago policy makers have been shifting toward banning traffic ticket quotas for police officers. In

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

[6]This is based off of reading work testimonials from Indeed.com.

2019, Illinois passed a law explicitly forbidding law enforcement agencies from evaluating personnel based on their ticket issuing productivity. Prior to the passage of the law, CPD had been criticized for mandating a minimum number of traffic stops (Main, 2017). To the best of my knowledge, any reference to ticket quotas by CPD were in relation to traffic infractions and not parking tickets. In fact, Figure 1 shows that the number of parking tickets issued by CPD fell by 44 percent from 2007 to 2011 and rose by 35 percent for PEA during the same time period.

3 Data

3.1 Parking Ticket Data

ProPublica Illinois in partnership with WBEZ Chicago obtained parking ticket data from the city of Chicago from 2007 - 2017 and released this data online. The data include information on the date and time of the ticket, where the vehicle was parked, and the badge number of the ticketing officer, de-identified license plates, make, model, and color of the vehicle, registration ZIP code, citation reason, and importantly, the payment status of the vehicle. 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 drivers' license suspension, and if the vehicle owner declared bankruptcy as a result of the ticket. It also includes information on how much of the fine remains unpaid, date of last payment, and the initial fine amount. I drop out of state vehicles from the data set as they are not required to comply with Chicago's city vehicle registration, which reduces the number of observations from 28 million to just over 20 million.

To construct my neighborhoods, I map each vehicle's parking location to a community area. Community areas were created by the Social Science Research Committee at the University of Chicago in beginning in the 1920s and the boundaries have remained unchanged beginning in 1980 (Society, 2005). Overall, there are 77 different Community areas in Chicago which the city also uses for official statistical and planning purposes.

Further, Census boundaries are tied to community areas. Using the Federal Communications Commission's block finder, I map each vehicle's parked location to a 2010 Census tract, which I can then match to a community area. I am able to match approximately 26 million of the original 28 million observations.

As an alternative specification, I use ZIP codes as my measure of neighborhoods. To determine if a ZIP code neighborhood is considered black or non-black, I 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 and 2012 - 2016. The ZCTA5 are approximate area representations of ZIP codes in the United States. ZCTA5's are not exact matches for ZIP codes since ZCTA5's are aggregated from Census blocks. Despite this, they are close matches for each other.

I also obtained sticker registration data by ZIP code using a Freedom of Information Act filed with the City Clerk of the city of Chicago. In order to protect the privacy of the purchasers, this information only contained the ZIP code of the buyer's billing address. The data set contained information of the date and time of the purchase, the full purchase amount, and the type of vehicle the sticker was for. I map each sticker purchase to a ZCTA5 using the ZIP code.

I augment my community area data using 2010 Census data. Specifically, I use information on the employment rate, the percentage of black residents, non-Hispanic white residents, and Hispanic non-white residents, the number of vehicles per household, and the per-capita income information. Similar to before, since the community areas are tied to Census areas, I merged the community area data to the Census data using the block FIPS code. As an alternative specification, I also use the 2011-2015 and the 2012-2016 ACS 5-Year estimates to control for any contemporaneous changes across community areas.

3.2 Employment data

To control for annual employment characteristics within a community area, I use the LEHD Origin-Destination Employment Statistics (LODES) data set released by the U.S. Census. The LODES data provide detailed spatial distributions of workers' employment and residential locations between two Census Block levels. The Census creates this data by combining Unemployment Insurance earnings data and the Quarterly Census of Employment and Wages data with administrative data, Census data, and survey data. The data set also disaggregates the information by age, industry, and earnings.

The LODES data set has some limitations. First, only employees covered by unemployment insurance are in the data set. Therefore self-employed individuals are not in the data set. Second, the workplace location is reported by the employer and so may not be correct for telecommuters or remote workers. Third, the data are only available up to 2015. Lastly, the data set is known to have issues with employees under reporting work site locations.

3.3 Descriptive Statistics

Table 2 shows the distribution of ticketed vehicle characteristics prior to 2012 in black neighborhoods compared to non-black neighborhoods. I define a neighborhood as black if the proportion of black residents within a community area is greater than 75 percent. I define a neighborhood as non-black if the proportion of black residents within a community area is less than or equal to 25 percent. Using these definitions of black and non-black and dropping the community areas that include the airports, I have 23 community areas defined as black and 40 community areas defined as non-black.[7]

In general, prior to the sticker tax increase, black neighborhoods faced worse outcomes in terms of parking ticket consequences compared to non-black neighborhoods. Specif-

[7] As a robustness check, I adjusted the threshold (to 1. %black $>$ 75% as black and % black $\leq$ 75% as non-black and 2. % black $>$ 50% as black and $\leq$ 50% as non-black) for determining whether a community area was black, but given the segregation of race by neighborhood, there are no significant changes in the results.

ically, 16 percent of the parking tickets in black neighborhoods were for the sticker tax whereas for non-black neighborhoods, only 6 percent of tickets were for the sticker tax, despite purchasing more stickers. Black neighborhoods paid \$10 more in initial fines per ticket with an average of \$71 per ticket. Possibly as a result of these higher average fines, cars ticketed in black neighborhoods are also less likely to pay on time. Conditional on receiving a ticket, cars ticketed in black neighborhoods are 50 percent less likely than cars in non-black neighborhoods to pay on time with only 27 percent of parking citations paid on time. I also find that the distribution of vehicle characteristics for ticketed cars to be different across both neighborhoods. Non-black neighborhoods have more luxury cars[8] and are less likely to have a temporary license plate. Cars parked in black neighborhoods are also more likely to be ticketed by Chicago police rather than by parking enforcement agents; specifically for black neighborhoods 60 percent of tickets came from CPD while 45 percent of tickets came from CPD for non-black neighborhoods. Vehicles ticketed in black neighborhoods also receive slightly more tickets in one day compared to non-black neighborhoods.

From Table 3, black neighborhoods have worse economic outcomes with lower per-capita income of nearly \$17,000 compared to non-black neighborhoods at over \$29,000 using data from the 2007 - 2011 5-Year ACS. This may be partially driven by the more than double unemployment rate of 24.5 percent. I also find that black neighborhoods have lower population compared to non-black neighborhoods. Further, by aggregating the data on number of vehicles per household from the 5-Year ACS, I estimate lower numbers of vehicle owned in black neighborhoods with 974 vehicles compared to 1727 vehicles in non-black neighborhoods but, given the population estimate, near equal vehicle ownership rates. I also find that non-black neighborhoods are composed mostly of non-Hispanic white residents with an average white population percentage of 57 percent.

Table 4 shows descriptive information of sticker purchasing behavior by black and non-black neighborhoods from 2007 to 2011. Interestingly, I find that non-black neigh-

[8] Luxury is defined by Kelley Blue Book.

borhoods purchase less than half as many stickers despite having more vehicles and a higher population, averaging only 2630 stickers per year. Black and non-black neighborhoods pay similar amount of fees on average and have similar distributions of sticker purchases by type of vehicles. Approximately 90.5 percent of sticker purchases are for passenger vehicles with curbside weight less than 4,500 pounds, and about 9% are for large passenger vehicles with curbside weight greater than 4,501 pounds. Non-black neighborhoods are significantly more likely to purchase stickers for motorbikes, but the percentage is quite small at less than 1 percent.

4 Empirical Strategy

4.1 Effect of the Sticker Increase

I first test if the increase in the sticker tax led to a disproportionate enforcement of the sticker tax in black neighborhoods compared to non-black neighborhoods after the fine increased in 2012. To test this hypothesis, I use an event study framework where my treatment variables are year dummies interacted with an indicator for a black neighborhood (using the definition outlined in section 3). Specifically, for each ticket i given in year t in community area c:

$$I(Sticker_{ict} = 1) = \alpha + \alpha_0 T_c + \sum_{\substack{t=2007 \\ t \neq 2011}}^{2017} \alpha_t (T_c \times Year_t) + \lambda_t + \sigma_m + \gamma_i + \epsilon_{ict} \tag{1}$$

where T_c is a dummy variable equal to one if community area c is black and zero if non black. λ_t and σ_m are year fixed effects and month fixed effects; γ_i is a vector of vehicle controls (type of vehicle and whether it's categorized as a luxury vehicle). The dependent variable is an indicator variable equal to one if the ticket i is for sticker non-compliance. Since tickets within the same community area are likely correlated to each other, I cluster my standard errors at the community area level. The coefficient of interest is α_t, which is the average difference in the probability of receiving the sticker fine between black and non-black neighborhoods in year t compared to 2011. If the sticker citation was disproportionately applied to black neighborhoods then $\alpha_t > 0$ for $t \geq 2012$.

Figure 2 shows my estimates of α_t at each year for 2007 - 2017 with 2011 being the omitted year. My results show that after the fine increased, black neighborhoods were 2 percentage points more likely to receive the sticker fine compared to non-black neighborhoods in the first year. The coefficient increases in the next few years to its highest level at 4.5 percentage points in 2015. Given that the difference in average probability of receiving the sticker fine between black and non-black neighborhoods prior to the fine increase was 10 percent, this implies the difference in likelihood increased by 20 percent to 50 percent, which I interpret as evidence of disparate application of the sticker citation on black neighborhoods after the increase.

The results of this identification strategy rely on two assumptions. The first is, in the absence of the increase in the fine, the trends in the probability of receiving the sticker citation would be parallel for black and non-black neighborhoods. This assumption cannot be directly tested, but I can test for parallel pre-trends by examining the estimated α_t for $t < 2011$. If the pre-trends were parallel, then these coefficient estimates will be insignificant and near zero. I find that only α_{2010} is near zero, but $\alpha_{2007-2009}$, while significant and negative, are much smaller in size when compared to α_t for $t > 2011$.

The second assumption is that there are no omitted time varying and neighborhood specific effects correlated to the timing of the policy. One possible explanation for the differential increase between black and non-black neighborhoods in the likelihood of receiving the sticker citation after the increase is that compliance also changed differentially across both types of neighborhoods. For example, if black neighborhoods decreased compliance relative to non-black neighborhoods then the increase in sticker citations are driven by the differential change in compliance rates, rather than disproportionate enforcement of the sticker citation. This is a plausible explanation especially because the cost of annual registration increased by \$10 that year. Further, since black neighborhoods have lower income on average than non-black neighborhoods, their compliance rates may decrease more than non-black neighborhoods. Even though the increase in the fine should increase compliance, income-constrained vehicle owners may not all be able to afford the higher cost of registration.

I test this alternative hypothesis by comparing the purchasing levels across neighborhoods using ZIP codes as the relevant neighborhoods. To determine what ZIP codes were considered black versus non-black, I use the 5-year ACS of 2007-2011, which has demographic information at the ZCTA5 level. If my results in Figure 2 are indeed driven by differential compliance across neighborhoods, than I should see a decrease in compliance for black neighborhoods compared to non-black neighborhoods. Since I do not know the rates of vehicle ownership, I proxy for compliance using sticker purchasing data. Therefore, for total sticker purchases in ZIP code z in year t:

$$Sticker\ Purchase_{zt} = 1 = \alpha + \alpha_0 T_z + \sum_{\substack{t=2007 \\ t \neq 2011}}^{2017} \alpha_t (T_z \times Year_t) + \lambda_t + \epsilon_{zt} \tag{2}$$

α_t will capture any differential changes across neighborhoods in purchasing behavior across time. I run the regression separately for purchases that paid the exact sticker registration fee and for those that paid more than the annual sticker registration fee. This is to proxy for on-time versus late purchases since late purchases required additional fees depending on how late the purchase was. I limit my sample to passenger and large passenger vehicles, which is approximately 98% of all purchases.[9] I also cluster my standard errors at the ZIP code level.

My results in Table 6 show that purchasing levels remain unchanged during 2007 - 2017. Columns (1) and (2) show the effect of the sticker price increase on total sales for large and small passenger vehicles for on-time and late purchases, respectively. When comparing the on-time purchases, or those that paid only the annual registration fee, I find that aside from increased compliance in 2012, that the difference in compliance rate

[9]The complete list of types of vehicles are motorbike, passenger, large passenger, and small truck. Since small truck was only added as an option after 2012, I only focus on passenger and large passenger vehicles. I also run the regression with all types of vehicles, with no difference in my estimates.

between black and non-black neighborhoods was relatively unchanged. The estimates are also positive, indicating that black neighborhoods were equally, if not more, likely to comply with the vehicle registration when compared to non-black neighborhoods. This implies that there was no differential change between both types of ZIP codes as a result of the sticker price increasing by $10 ($15) for small (large) passenger vehicles.

For late purchases in Column (2), or purchases where the buyer paid more than the annual fee, I find positive estimates. This implies that the number of late sticker purchases increased more for black neighborhoods compared to non-black neighborhoods after 2012. One possible explanation is that the higher sticker enforcement in black neighborhoods resulting from the 2012 increase led to more drivers to pay the sticker fee as a result of receiving the sticker citation. Both the results in Column (1) and Column (2) show that differential compliance rates between black and non-black neighborhoods is not driving the disparate sticker enforcement.

When I use total revenue as my measure of sticker purchases across black and non-black neighborhoods in Column (3), I find that the revenue significantly rises more for black ZIP codes compared to non-black ZIP codes. This rise in revenue translates to a per-capita increase of $1.63 to $2.55 in annual sticker purchases.[10] This provides suggestive evidence that the disparate sticker enforcement also led to a higher increase in revenue from sticker purchases in black neighborhoods, than non-black neighborhoods.

4.2 Robustness Checks

To ensure my results in Table 6 and Figure 2 are not driven by my definition of neighborhood, I also re-estimate Equation 1 using ZIP codes as the relevant neighborhood measure. Table 5 shows the coefficient estimates using community areas in Column 1 and ZIP codes in Column 2 for α_t. I find that these coefficients are not significantly different from another. Thus, my choice of neighborhood measure is not driving the re-

[10] The average population of black ZCTA5 is 31,557.

sults.[11]

Since the 2012 budget proposal also entailed changes in the city's debt collection practices, I also add controls for employment levels within community area using the LODES data from 2007 to 2015 to ensure that my results are not driven by differential changes in employment across black and non-black community areas. One concern is that these policies may have negatively affected the employment levels across community areas, especially city workers. Table 7 shows the results without employment controls in Column (1), controlling for percentage employed in Column (2), and controlling for percentage employed with low (monthly earnings less than $1250) or medium earnings (monthly earnings greater than $1251 but less than $3333).[12] I find that my coefficients of interest, α_t, do not change significantly with or without controls for employment or employment by earnings.

The changes in the debt collection policies may have also disproportionately changed residents' ability to purchase stickers across black and non-black neighborhoods. To account for this, I also include controls for the number of late and on-time sticker purchases in ZIP code z in a year-month. My results in Table 8 show no significant changes in α_t.

Lastly, I use the 2007-2011 and the 2012-2016 5-Year ACS to control for demographic changes. Given that my identification strategy relies on no other contemporaneous changes across black and non-black neighborhoods at 2012, I include controls for employment, income, demographic characteristics, and controls for purchasing behavior. Since I do not have annual estimates of population changes at the neighborhood level, I use an indicator variable for whether the ticket was issued after 2012 instead of year dummies. My results in Table 9 show that the disparate enforcement is robust to the inclusion of these controls. Column (1) shows the estimate of a 4 percentage point increase in the likelihood of receiving the sticker fine in black neighborhoods compared to non-

[11] I prefer using community area as my measure of neighborhood as the definitions have been the same since 1989, while ZCTA5 definitions changed in 2010 with the Census.

[12] Percentage employed is the total number of employed divided by the total number in the labor force. Total employed data is from the LODES data while total number in the labor force is from the 2011-2015 and 2012 - 2016 5-Year ACS.

black neighborhoods after 2012, with no controls. Column (2) includes community area characteristic controls with no significant change in the estimate. Column (3) includes ZIP code characteristic controls and the number of late and on-time sticker purchases in ZIP code z in year t. I find that the disparate enforcement observed in Column (1) to be robust to these controls, with similar estimates. On average, police officers were 34 to 42 percent more likely to give the sticker citation after the 2012 fine increase to black neighborhoods than non-black neighborhoods.

4.3 Comparing CPD and PEA's ticketing behavior

While PEA and CPD have many differences in their jobs, one major difference in the context of parking citations, is that PEA are evaluated based on their ticketing productivity. As suggested by past research, these evaluations will influence PEA's to behave as agents of revenue maximizing principals (Makowsky and Stratmann, 2009). Thus, by comparing both types of agents' ticketing behavior I can test if CPD's disparate enforcement is revenue-maximizing. If PEA's sticker productivity across neighborhoods changes similarly to CPD's behavior, this may imply that the disproportionate increase in sticker citations in black neighborhoods is a result of revenue-maximizing behavior, and not disparate enforcement.

In order to test this, I re-estimate Equation 1 for both types of agents separately. Figure 3 plots the estimates for the interaction between black community areas and year dummies separately for tickets by PEA and CPD. My results show that PEA do not consistently more strongly enforce sticker compliance in black neighborhoods and only do so in 2012 and 2013. Further, the estimates for PEA in 2013 are significantly less than the estimates for CPD. The estimates for CPD are similar to the estimates in Figure 2, implying that the disproportionate application of the sticker fine is driven by CPD's ticketing behavior. I interpret the contrast in results between PEA and CPD as suggestive evidence that using ticket productivity in evaluating work performance increases the agents revenue maximizing behavior. These results are also robust to using ZIP codes as the definition of my neighborhoods.

I also test if the disproportionate rise in sticker citations by police officers is driven by increasing enforcement of sticker compliance or by the de-emphasizing of the other types of tickets. If the latter is true, this could imply that police officers are revenue-setting agents and the sticker increase causes police officers to switch to the more expensive ticket while maintaining their revenue targets. Therefore, for total sticker citations or non-sticker citations in community area c given in year t:

$$Ln(Tickets_{ct}) = \alpha + \alpha_0 T_c + \sum_{\substack{t=2007 \\ t \neq 2011}}^{2017} \alpha_t (T_c \times Year_t) + \lambda_t + \epsilon_{ct} \tag{3}$$

will describe the percentages changes in the ticket behavior for police officers and parking enforcement officers. The dependent variable, $Ln(Tickets_{ct})$, is the natural log of total of tickets (both sticker only and non-sticker only) issued in community area c in year t. Columns (1) and (2) of Table 10 show that the percentage change in number of sticker citations and non-sticker citations issued by CPD, respectively. I find that the total non-sticker tickets also increased significantly after 2012, which implies that while police officers were issuing more sticker citations, they were not reducing their productivity for other types of parking violations.

For PEA, I find that the percentage change in sticker citations, shown in Column (3), is not similar to the pattern observed in by CPD in Column (2). This is unsurprising given the results in Figure 3. Further, I find that the percentage change in non-sticker tickets closely matches the pattern for the percentage change in total sticker tickets. Thus, the increases in sticker enforcement by PEA shown in Figure 3 may be driven by increasing total ticketing in black neighborhoods compared to non-black neighborhoods after 2012.

4.4 Effect of Increase as a Per-Capita Tax

One important question is how the disproportionate sticker citations affected the expected per-capita parking tax between black and non-black neighborhoods. In order to estimate this, I aggregate the total revenue from the initial fine to the community area level by year and use the total revenue divided by total population as my measure of per-capita tax. Therefore, for parking tickets given in community area c in year t:

$$P_{ct} = \alpha + \alpha_0 T + \sum_{\substack{t=2007 \\ t \neq 2011}}^{2017} \alpha_t (T_c \times Year_t) + \lambda_t + \epsilon_{ct} \tag{4}$$

where P_{ct} is the total expected fines from parking tickets given in community area c in year t divided by the community area population. Table 11 show the estimates for the expected per-capita tax revenue in Column (1). I find that the per-capita parking tax for residents within black community areas increases significantly more than residents in non-black community areas. Within the first year, the per-capita tax rose by \$5.23, which is approximately a 20% increase. At its peak, the per-capita expected revenue rose by \$13.36, which is a 50% increase in 2013.

Given that black community areas have lower household income, I also estimate the actual per-capita revenue, using the total payments for a parking ticket given in year t in community area c divided by the population in the community area.[13] If the actual revenue is less than the expected revenue, this may predict that black neighborhoods may be less likely to pay on time, exposing to Chicago's punitive parking system. My estimates show that residents within black neighborhoods were initially able to increase their per-capita tax by \$2.67 to \$5.66 in 2012 and 2013, which is equivalent to a 11 percent to 23 percent increase. The actual increase in revenue is significantly lower than the expected revenue. By 2015, actual revenue did not increase, despite the expected revenue increasing by \$11.86. Further, in 2016, and 2017, actual revenue declines in black neighborhoods when compared to non-black neighborhoods. This may provide suggestive evidence that the increase in expected revenue reduced their ability to pay their parking tickets and lead to higher debt, which further reduced their ability to pay future tickets.

[13] My measure of total population within the community area is aggregated from the population by Census blocks from the 2010 Census.

5 Conclusion

In this paper, I use detailed administrative parking citation data from the City of Chicago and exploit a fine increase for failing to display the city sticker to provide evidence of disparate enforcemet. I find that Chicago police were 20 to 50 percent more likely to give sticker citations to vehicles parked in black neighborhoods compared to vehicles parked in non-black neighborhoods. The effect is robust to controls for annual employment levels and is not driven by changing sticker compliance across neighborhoods.

I also compare the ticketing behavior between parking enforcement agents and Chicago police and find that parking enforcement agents do not disparately enforce the sticker citation. I interpret this as evidence that the behavior observed by Chicago police is indeed disparate enforcement. I attribute this difference to the fact that parking enforcement agents are explicitly evaluated based on their productivity and efficiency whereas Chicago police are not. I interpret this as suggestive evidence in line with the findings from Makowsky and Stratmann (2009). Further, that without the evaluations, police officers base their ticketing choices on their own preferences, which suggests that this disparate enforcement may be motivated by racial bias.

Ultimately, this disproportionate enforcement is harmful not only for the Chicago's revenue, but also for black residents. I show that after 2014, vehicles parked in black neighborhoods generated less per-capita revenue than vehicles parked in non-black neighborhoods. This could lead to further consequences for black residents that escalate as a result of Chicago's punishing parking payment system and debt collection policies further reducing the city's revenue.

6 Appendix

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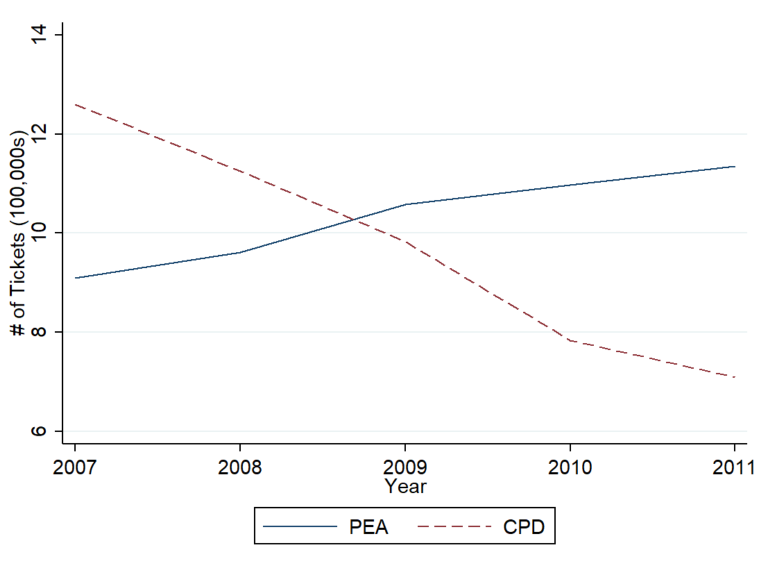
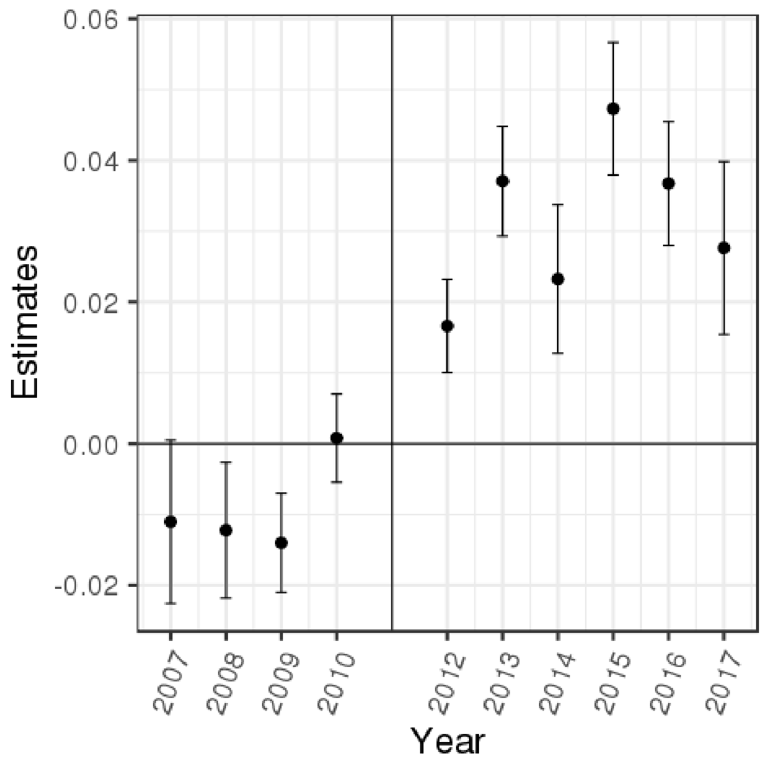
6.1 Figures

Figure 1: Annual Number of Tickets from CPD and PEA



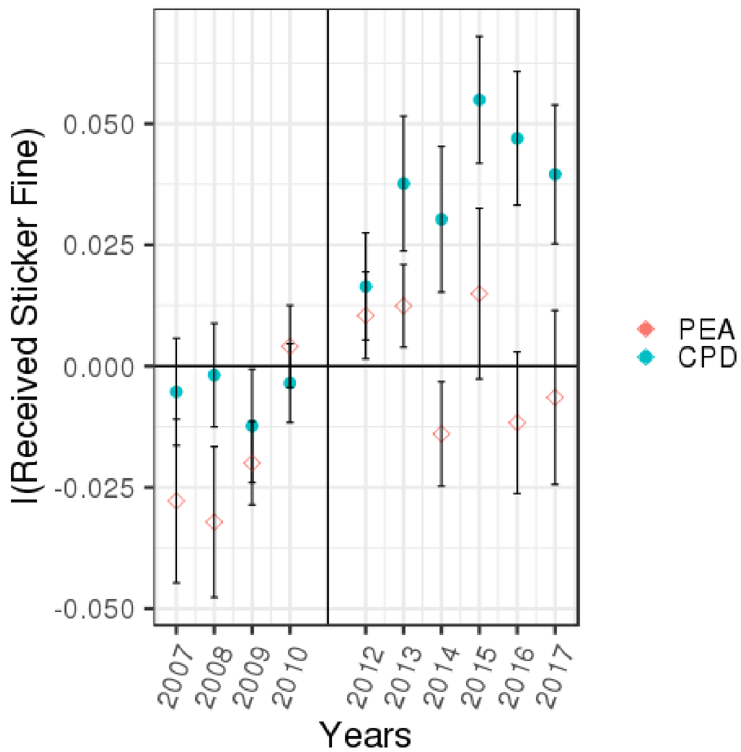
Notes: Dash line shows the average number of tickets issued per year by Chicago police (CPD). Solid line shows the average number of tickets issued per year by parking enforcement (PEA). Average, unweighted ticket counts for a given year from January 2007 to December 2011.

Figure 2: Evidence of Disparate Treatment



Notes: Coefficient for the estimated increase in the probability of receiving the sticker fine for black neighborhoods compared to white neighborhoods. 95 percent confidence intervals are shown and standard errors are clustered at the community area level.

Figure 3: Ticketing Behavior of CPD compared to PEA



Notes: Filled dots show the coefficient estimates of α_t from Equation (1) for Chicago Police Department (CPD); empty dots show the coefficient estimates from Equation (1) for parking enforcement agents (PEA). 2011 is the omitted year.

6.2 Tables

Table 1: Popular Fines

Top 7 Fines from 2007 - 2017

Violation Code	Description	Fine	2007 - 2011	2012 - 2017
0976160F	Expired plates or temporary registration	60	1	1
0964190A	Exp. meter non-central business district	50	2	3
0964040B	Street cleaning	60	3	2
0964125B	No city sticker vehicle $\leq$ 16,000 lbs.	125/200	4	4
0964090E	Residential permit parking	75	5	5
0976160A	Rear and front plate required	60	6	7
0964150B	Parking/standing prohibited anytime	75	7	6

Violations are ranked by number of citations in a given time period. I omitted vehicles with out of state license plates.

Table 2: Ticket Outcomes by Neighborhood

	% Black ≤ 0.25	% Black > 0.75
% Sticker	6.70	16.52
	(25.01)	(37.14)
Initial Fine Amount	60.35	70.95
	(28.09)	(36.13)
Luxury Car	16.87	12.82
	(37.45)	(33.43)
Ticketed by CPD	45.07	62.03
	(49.76)	(48.53)
% Paid on Time	54.39	27.29
	(49.81)	(44.53)
# Of Tickets	1.04	1.12
	(0.220)	(0.385)
Total Tickets	15,998,754	4,598,240

23 community areas have Black Pop > 0.75, 40 have Black Pop ≤ 0.25. Descriptive statistics only shown for tickets given from January 2007 to December 2011. Unweighted means and standard deviations (in parentheses) are shown.

Table 3: Descriptive Neighborhood Statistics

	% Black ≤ 0.25	% Black > 0.75
Per-capita Inc	29,380	16,550.7
	(16,414)	(5059)
Unemployment Rate	11.485	24.561
	(4.272)	(5.101)
# of Vehicles	1727.49	974.32
	(858.78)	(672.69)
% White	57.06	2.84
	(27.49)	(4.63)
Population	40,127.07	26,573
	(23,749.57)	(21,197.67)

23 community areas have % Black > 0.75, 40 have % Black ≤ 0.25. Descriptive statistics only shown for tickets given from January 2007 to December 2011. Unweighted means and standard deviations (in parentheses) are shown.

Table 4: Sticker Purchases by Black and Non-Black Neighborhoods Pre-2012

Obs. Char.			
	% Black ≤0.25	% Black >0.75	Δ
Annual # of Sales	2630.806	5409.962	-2779.156
	(7481.67)	(6960.86)	(-3.861)
Average Sale Price	82.18	81.408	.772
	(13.969)	(7.915)	(.866)
% Paid Extra Fee	16.301	14.049	2.252
	(24.624)	(12.052)	(1.594)
% Large Passenger Vehicle	8.937	9.389	-.452
	(19.094)	(10.037)	(-.392)
% Passenger Vehicle	90.455	90.456	-.001
	(19.287)	(10.015)	(-.001)
% Motorbike	.608	.155	.453
	(3.337)	(.186)	(4.208)
Average Total # of Sales	29896.4	34269.5	

Unweighted means and standard deviations are shown in columns 1- 3. In column 4, Z scores are in parentheses. Summary statistics are calculated using pre-2012 years only

Table 5: Evidence of Disparate Sticker Enforcement

	Dependent variable:	
	I(Sticker)	
	Community Area	ZIP Code
T	0.092***	0.094***
	(0.008)	(0.007)
$I(Year = 2007)$	0.002	0.002
	(0.002)	(0.002)
$I(Year = 2008)$	−0.001	−0.00001
	(0.002)	(0.002)
$I(Year = 2009)$	−0.001	0.0001
	(0.002)	(0.002)
$I(Year = 2010)$	−0.002	−0.001
	(0.001)	(0.001)
$I(Year = 2012)$	0.008***	0.007***
	(0.001)	(0.001)
$I(Year = 2013)$	0.008***	0.008***
	(0.002)	(0.001)
$I(Year = 2014)$	−0.005***	−0.005***
	(0.002)	(0.001)
$I(Year = 2015)$	0.012***	0.011***
	(0.002)	(0.001)
$I(Year = 2016)$	0.017***	0.015***
	(0.002)	(0.002)
$I(Year = 2017)$	0.028***	0.027***
	(0.004)	(0.003)
$I(Year = 2007) \times T$	−0.011**	−0.012**
	(0.006)	(0.008)
$I(Year = 2008) \times T$	−0.012***	−0.015***
	(0.005)	(0.003)
$I(Year = 2009) \times T$	−0.014***	−0.018***
	(0.004)	(0.003)
$I(Year = 2010) \times T$	0.001	0.0002
	(0.003)	(0.004)
$I(Year = 2012) \times T$	0.017***	0.016***
	(0.003)	(0.003)
$I(Year = 2013) \times T$	0.037***	0.039***
	(0.004)	(0.005)
$I(Year = 2014) \times T$	0.023***	0.024***
	(0.005)	(0.007)
$I(Year = 2015) \times T$	0.047***	0.049***
	(0.005)	(0.006)
$I(Year = 2016) \times T$	0.037***	0.037***
	(0.004)	(0.005)
$I(Year = 2017) \times T$	0.028	0.030
	(0.006)	(0.008)
Constant	0.010	0.014*
	(0.008)	(0.008)
Observations	20,427,278	17,020,190

*p<0.1; **p<0.05; ***p<0.01. T is an indicator variable equal to one if the community area or ZIP code has more than 75% black residents and equal to 0 if less than 25% residents. Standard errors are clustered at the community area or ZIP code level. Both regressions include month fixed effects, vehicle type fixed effects, and controls for if the vehicle was considered luxury or not.

Table 6: Total Sticker Purchases

	(1) On-time Purchases	(2) Late Purchases	(3) Total Revenue
T_z	1014.24**	−17.32	75221.32**
	(396.43)	(122.17)	(34387.71)
$T\_z \times I(Year = 2007)$	−785.08	23.77	−62630.11
	(480.24)	(156.61)	(51219.36)
$T\_z \times I(Year = 2008)$	−99.83	121.23	652.18
	(127.10)	(119.41)	(18402.00)
$T\_z \times I(Year = 2009)$	131.82	−38.12	2023.08
	(117.97)	(62.74)	(13682.96)
$T\_z \times I(Year = 2010)$	66.42	58.30	11743.62
	(99.37)	(54.58)	(12619.81)
$T\_z \times I(Year = 2012)$	316.33**	98.04	51625.65**
	(146.73)	(60.64)	(23763.64)
$T\_z \times I(Year = 2013)$	217.07	163.21**	54503.63**
	(149.86)	(70.96)	(25352.54)
$T\_z \times I(Year = 2014)$	63.97	634.35**	62172.11***
	(238.52)	(296.39)	(22354.25)
$T\_z \times I(Year = 2015)$	61.20	454.69***	75837.42***
	(203.38)	(167.56)	(22622.08)
$T\_z \times I(Year = 2016)$	341.49*	424.64***	90548.06***
	(189.57)	(153.65)	(25190.49)
$T\_z \times I(Year = 2017)$	330.41*	343.27**	80641.86***
	(184.86)	(136.10)	(23022.47)
I(Passenger Vehicle)	2328.27***	806.41***	253927.85***
	(430.78)	(153.75)	(47715.69)
Constant	−3455.14***	−1329.23***	−432402.67***
	(602.00)	(227.19)	(73916.05)
Observations	3720	3720	3720

*p<0.1; **p<0.05; ***p<0.01. Regression includes year fixed effects and controls for vehicle type. Standard errors are clustered on the ZIP code level. $T_z = 1$ if the ZIP code's black to total population ratio is greater than 0.75 and 0 if the ratio is less than or equal to 0.25. Using that definition, 287 ZIP codes are non-black ($T_z = 0$) and 23 are black ($T_z = 1$). A sticker purchase is considered on-time if only the exact amount of the sticker was paid. A purchase is considered late if the purchase included extra fees on top of the original sticker price.

Table 7: Controlling for Employment

	(1)	(2)
	Dependent Variable: I(Sticker)	
T_c	0.090***	0.076***
	(0.008)	(0.008)
$T_c \times I(Year = 2007)$	−0.007	0.003
	(0.006)	(0.007)
$T_c \times I(Year = 2008)$	−0.009*	−0.003
	(0.005)	(0.006)
$T_c \times I(Year = 2009)$	−0.013***	−0.003
	(0.004)	(0.005)
$T_c \times I(Year = 2010)$	0.003	0.004
	(0.004)	(0.004)
$T_c \times I(Year = 2012)$	0.018***	0.023***
	(0.004)	(0.004)
$T_c \times I(Year = 2013)$	0.038***	0.041***
	(0.004)	(0.004)
$T_c \times I(Year = 2014)$	0.024***	0.027***
	(0.005)	(0.005)
$T_c \times I(Year = 2015)$	0.046***	0.048***
	(0.005)	(0.005)
% Employed		−0.092***
		(0.019)
Constant	0.000	0.000
	(0.004)	(0.003)
Observations	14393050	14393050

*p<0.1; **p<0.05; ***p<0.01. Regression includes year fixed effects and controls for vehicle type. Standard errors are clustered an the community area level. $T_c = 1$ if the community area's black to total population ratio is greater than 0.75 and 0 if the ratio is less than or equal to 0.25. Employment data is at the year-tract level and is from the LODES data.

Table 8: Controlling for Sticker Purchases

	(1)	(2)	(3)
	Dependent Variable: I(Sticker)		
T_z	0.091***	0.090***	0.093***
	(0.007)	(0.007)	(0.007)
$T_z \times I(Year = 2007)$	−0.010	−0.009	−0.009
	(0.006)	(0.006)	(0.006)
$T_z \times I(Year = 2008)$	−0.012**	−0.012**	−0.012**
	(0.005)	(0.005)	(0.005)
$T_z \times I(Year = 2009)$	−0.014***	−0.014***	−0.014***
	(0.003)	(0.003)	(0.003)
$T_z \times I(Year = 2010)$	0.001	0.001	0.000
	(0.003)	(0.003)	(0.003)
$T_z \times I(Year = 2012)$	0.017***	0.017***	0.017***
	(0.003)	(0.003)	(0.003)
$T_z \times I(Year = 2013)$	0.037***	0.038***	0.037***
	(0.004)	(0.004)	(0.004)
$T_z \times I(Year = 2014)$	0.023***	0.023***	0.023***
	(0.005)	(0.005)	(0.005)
$T_z \times I(Year = 2015)$	0.047***	0.047***	0.047***
	(0.005)	(0.005)	(0.005)
Total Sales/Total Population		−26.349***	
		(6.297)	
% Late Purchases			0.000*
			(0.000)
% On time Purchases			0.000***
			(0.000)
Constant	0.000	0.000	−0.029***
	(0.003)	(0.003)	(0.005)
Observations	20250679	20250679	20250679

*p<0.1; **p<0.05; ***p<0.01. Regression includes year and month fixed effects and controls for vehicle type. Standard errors are clustered an the ZIP code level. $T_z = 1$ if the ZIP code's black to total population ratio is greater than 0.75 and 0 if the ratio is less than or equal to 0.25. Ticket purchase data is aggregated to the year-month ZIP code level. A purchase is defined as late if the the seller paid more than the annual registration fee and on time if the seller paid the exact amount.

Table 9: Robustness check: controlling for population changes

	Dependent variable:		
	I(Sticker)		
	Community Area	Community Area	ZIP Code
	(1)	(2)	(3)
$T \times I(After)$	0.037***	0.033***	0.033***
	(0.004)	(0.004)	(0.004)
T	0.088***	0.101***	0.097***
	(0.008)	(0.017)	(0.016)
$I(After)$	0.011***	0.012***	0.010***
	(0.002)	(0.002)	(0.002)
HH income		−0.00000	−0.00000**
		(0.00000)	(0.00000)
% Employed		−0.138*	−0.159***
		(0.071)	(0.047)
%White		0.002	0.012
		(0.031)	(0.020)
% Black		−0.060**	−0.052**
		(0.025)	(0.021)
# Late Purchases			0.00001***
			(0.00000)
# On-Time Purchases			0.00000***
			(0.00000)
Constant	0.012	0.131***	0.136***
	(0.008)	(0.034)	(0.023)
Observations	20,580,135	20,580,135	20,233,824
R^2	0.045	0.049	0.049

*p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered an the community area level in Columns (1) and (3) and at the ZIP code level in Column (2). $T = 1$ if the community area's (ZIP code's) black to total population ratio is greater than 0.75 and 0 if the ratio is less than or equal to 0.25. HH Income, % Employed, % White, %Black are from the 2007-2011 or the 2012-2016 5-Year ACS. $I(After)$ is an indicator variable equal to one if the ticket was issued after 2011 and 0 otherwise. $\#Late\ Sticker$ and $\#On-Time\ Sticker$ are annual sticker purchases within a year within a ZIP code.

Table 10: Effect on Non-Sticker Citation Productivity

	(1)	(2)	(3)	(4)
	CPD		PEA	
	Ln(Total Sticker)	Ln(Total Non-Sticker)	Ln(Total Sticker)	Ln(Total Non-Sticker)
T_c	0.187	-0.548^{**}	-0.713^{***}	-1.466^{***}
	(0.268)	(0.275)	(0.250)	(0.285)
$T_c \times I(Year = 2007)$	-0.188^{*}	-0.156^{***}	-0.292^{***}	-0.043
	(0.096)	(0.055)	(0.092)	(0.107)
$T_c \times I(Year = 2008)$	-0.105	-0.148^{**}	-0.065	0.177^{**}
	(0.120)	(0.070)	(0.059)	(0.079)
$T_c \times I(Year = 2009)$	-0.247^{**}	-0.191^{***}	0.073	0.144^{**}
	(0.102)	(0.063)	(0.077)	(0.068)
$T_c \times I(Year = 2010)$	-0.080	-0.101^{**}	0.162^{***}	0.128^{***}
	(0.090)	(0.051)	(0.053)	(0.048)
$T_c \times I(Year = 2012)$	0.292^{***}	0.206^{***}	0.130^{**}	0.133^{**}
	(0.075)	(0.053)	(0.061)	(0.057)
$T_c \times I(Year = 2013)$	0.346^{***}	0.282^{***}	0.364^{***}	0.216^{***}
	(0.108)	(0.073)	(0.070)	(0.068)
$T_c \times I(Year = 2014)$	0.556^{***}	0.359^{***}	0.296^{***}	0.233^{***}
	(0.113)	(0.066)	(0.097)	(0.072)
$T_c \times I(Year = 2015)$	0.617^{***}	0.399^{***}	0.108	0.104
	(0.114)	(0.072)	(0.079)	(0.064)
$T_c \times I(Year = 2016)$	0.561^{***}	0.354^{***}	-0.285^{**}	-0.170
	(0.119)	(0.076)	(0.126)	(0.116)
$T_c \times I(Year = 2017)$	0.266^{**}	0.199^{**}	-0.216^{*}	0.003
	(0.126)	(0.077)	(0.122)	(0.096)
Constant	6.025^{***}	8.400^{***}	6.748^{***}	8.963^{***}
	(0.131)	(0.186)	(0.148)	(0.206)
Observations	946	946	946	946

*p<0.1; **p<0.05; ***p<0.01. The unit of observation is community area by year. Standard errors are clustered at the community area level. The dependent variable in Columns 1 and 3 is the natural log of total sticker citations given in t in community area c. The dependent variable in Columns 2 and 4 is the natural log of total non-sticker citations in year t in community area c. Columns (1) and (2) are restricted to tickets issued by CPD and Columns (3) and (4) are restricted to PEA only.

Table 11: Effect on per-capita Revenue for Parking

	(1)	(2)
	Per Capita Revenue	
	Expected	Actual
T_c	-12.03^{**}	-13.86^{**}
	(5.85)	(5.58)
$T_c \times I(Year = 2007)$	0.99	1.77
	(1.40)	(1.36)
$T_c \times I(Year = 2008)$	-0.36	0.80
	(1.57)	(1.53)
$T_c \times I(Year = 2009)$	-4.06^{***}	-2.85^{**}
	(1.44)	(1.32)
$T_c \times I(Year = 2010)$	-1.90^{*}	-1.23
	(1.11)	(0.95)
$T_c \times I(Year = 2012)$	5.23^{***}	2.67^{**}
	(1.53)	(1.17)
$T_c \times I(Year = 2013)$	13.36^{***}	5.66^{***}
	(3.31)	(2.05)
$T_c \times I(Year = 2014)$	12.58^{***}	4.31^{**}
	(2.75)	(1.68)
$T_c \times I(Year = 2015)$	11.86^{***}	1.28
	(2.57)	(1.18)
$T_c \times I(Year = 2016)$	4.37^{*}	-4.10^{***}
	(2.32)	(1.12)
$T_c \times I(Year = 2017)$	-0.15	-6.48^{***}
	(1.65)	(1.65)
Constant	38.83^{***}	38.05^{***}
	(5.22)	(5.11)
Observations	946	946

*p<0.1; **p<0.05; ***p<0.01. The unit of observation is community area by year. Standard errors are clustered at the community area level. The dependent variable in Column 1 is the sum of fines for all tickets given in year t in community area c divided by the 2010 Census population. Column 2 is the total amount paid for a fine given in year t in community area c divided by the 2010 Census Population.