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Essays on the Economics of Police Officer Discretionary Decisions

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ESSAYS ON THE ECONOMICS OF POLICE OFFICER DISCRETIONARY DECISIONS

By

Huong Diem Nguyen

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This dissertation consists of three chapters studying police officer discretionary decisions on traffic stops and traffic violations. The decisions include whether to stop and search a vehicle, whether to write a ticket or a warning, the duration of stop, and the fine amount. The purpose of this research is to determine whether police officer discretion is affected by various factors other than the violation itself.

The first chapter investigates the influence of driver characteristics on police officer discretionary decisions. The study uses data of citations, both written warnings and tickets, for traffic violations recorded by Massachusetts police officers in April and May 2001. The variable measuring police officer discretionary behavior is created by subtracting the suggested law amount from the actual fine amount written on traffic citations. The study finds that police officers are more lenient toward female drivers, old drivers, in-town drivers, and in-state drivers than male drivers, middle-aged drivers, out-of-town drivers, and out-of-state drivers, respectively. In addition, using quantile fixed effects models, the study shows that these effects vary across quantiles of police officer discretion.

The study then investigates other factors influencing police officer discretionary behavior. First, examining police officer decisions within an hour or a day, we show that police officers are more likely to issue a lower fine or a warning to a driver after issuing a ticket instead of a warning during the previous stop. Second, the study

finds that although police officers are stricter at the end of month than other times of the month, the difference is minimal. We, therefore, conclude that the conventional wisdom of a "ticket quota" does not exist.

The second chapter explores the effect of police officer characteristics on their discretionary decisions. The data includes all traffic citations written by Boston police officers in April and May 2001. The study shows that female, black, Asian, or experienced police officers are more likely to issue higher fine than male, white, or less-experienced police officers, respectively. The study also finds that white drivers are treated with the most leniency regardless of police officer race. Black and Hispanic officers give more favor to drivers of their same race. In addition, Asian police officers are the strictest compared to other police officers.

The third chapter investigates police officer discretionary behavior in stop and search decisions. The study examines not only search and success rates of finding contraband but also the probability of being ticketed as well as the duration of stops. We use statewide data of all traffic stops in Illinois in 2012 and find that police officers are less likely to find contraband in searches from female and senior drivers compared to searches from male drivers and drivers of other age groups, respectively. This suggests that police officers are stricter with female drivers and drivers aged older than 51. We then use police department fixed effects to estimate the effects of driver characteristics on police officer discretionary decisions regarding the duration of stops. Here we find opposite results. Police officers are more lenient toward both female and older drivers than they are toward male and middle-aged drivers, respectively. Younger drivers aged 16-21 and 21-30 are stopped longer than middle-aged drivers. Using three methods: the success rate of finding contraband, police officer agency fixed effects method, and the propensity score matching method, we find that police officers treat white drivers more leniently than drivers of other races.

In general, the dissertation shows that extra-legal factors such as race, gender, age, and resident status of drivers and race, gender, and working experience of police officers influence police officer discretionary decisions. Our findings and conclusions have important policy implications regarding the management of police officer discretionary decisions since the use of such factors may have ill effects on public trust and undermine the legitimacy of laws. We suggest that each police department should have a training program to educate officers about the outcomes and consequences of their decisions. In addition, the training must be supported by close supervision in order to ensure desired behavior.

To my parents, Hoa Thi Pham and Tai Nguyen

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CHAPTER 1
Introduction

1.1 Discretion

Discretion is the power to decide what should be done in a particular situation. Discretion exists when a decision maker has the power not only to choose to take an action but also to enforce the limits of such an action. In criminal justice, discretion can be understood as the right of an official to make decisions that extend beyond the legal mandate. The goal is to ensure the fair administration of justice. When exercising discretion, decision-makers need to consider all relevant factors and act reasonably and equally. Although it is important for decision makers to consider each case on its own merits, they must not make the decisions based on their own preference.

In criminal justice, police officers, prosecutors, and judges have discretionary power to decide where guilt lies, who needs to be punished, and what the penalty should be. For the same violation, the penalty can be the same or different due to various factors such as the nature of the offense, the characteristics of the offenders, and constitutional laws dealing with the case. Criminal justice is, therefore, best understood by studying the behavior of individual decision makers.

While discretion is an essential and unavoidable aspect of effective law enforcement work, the misuse of discretion can raise public concerns about the legitimacy of police officer decisions. In Dallas, Texas in 2009, Ernestina Mondragon, a 49 year-old female, was pulled over for an illegal U-turn and failing to present her driver's license.[1] Besides the fine for both violations, she was fined an extra $204 for being a "non-English

[1] "Dallas police apologizes over fine for "non English-speaking driver" ", The Guardian, Sunday 25 October 2009.

speaking driver".[2] Later, she contested and the court dropped the charge. David Kunkle, the Dallas police chief, apologized at a press conference. He admitted that over the last three years more than twenty police officers had issued thirty eight tickets with the same type of surcharge. He promised those previous surcharges would be dismissed and, if already paid, reimbursed. This is one in many cases that police officers misuse their discretion.

Misuse of discretion can lead to unequal treatments between citizens, which is prohibited under the law. According to the Equal Protection Clause, the Fourteenth Amendment to the United States Constitution, everyone has equal protection of the law.[3] If a police officer uses his discretionary power to make decisions based on personal preferences, that behavior is inconsistent with the intent of the law.

Analyzing discretion in police officer decisions is important because of its extensive effects on daily lives. Warren E. Burger, Chief Justice of the United States stated that "The policeman on the beat or in the patrol car makes more decisions and exercises broader discretion affecting the lives of people every day and to a greater extent, in many respects, than a judge will ordinarily exercise in a week".[4] Discretion is a day-to-day working tool with which police officers evaluate complex situations and apply laws to arrive at appropriate solutions. Discretion is therefore an essential and unavoidable aspect of effective police work. Although broad and detailed, the law cannot cover all contingencies and ramifications of the real world. Law enforcement officers, therefore, need to adjust their decisions on a case-by-case basis.

[2] In Texas, there is federal statue requiring drivers of commercial vehicles to be able to speak English; but not for private drivers

[3] Section one in the Fourteenth Amendment states that "All persons born or naturalized in the United States, and subject to the jurisdiction thereof, are citizens of the United States and of the State wherein they reside. No State shall make or enforce any law which shall abridge the privileges or immunities of citizens of the United States".

[4] Address to local and state police administrators up on their graduation from the FBI, reported in Frank J. Remington, Standards Relating to the Urban Police Function, American Bar Association: Advisory Committee on the Police Function, (1972), p. 2.

1.2 Police officer discretion and traffic stops

Traffic stops are the most common reason that police officers interact with the public. It is likely that drivers may violate traffic rules at some time when driving and police officers have the power to decide who to stop since not all drivers who violate traffic laws are stopped. To stop a vehicle, a police officer must have reasonable suspicion or legal justification. Decisions that are influenced by factors such as driver race, gender, and age cannot serve as valid justification in the court of law and violate the Fourth Amendment of the Constitution, which specifically protects against unauthorized searches and seizures.

Police officer discretionary behavior in stop and search decisions and decisions on traffic violations are somewhat different by nature. Given probable cause, police officers may stop any vehicle even when a driver has not violated any specific traffic law. Police officers can then use their discretion to decide to search the vehicle. The nature of the contraband, if found, will decide the fine. Police officers have less discretion on deciding the penalty if they find drug, contraband, or illegal property. On the other hand, when a driver violates a traffic law and is pulled over by a police officer, the police officer has full discretion regarding whether or not to issue a ticket, a written warning, or an oral warning. If the police officer decides to give a ticket, the amount of the fine may also fall within the discretionary power of the police officer.

This dissertation investigates what influences officer discretionary decisions in two instances: the penalty for traffic violations and the decision to stop and search vehicles. Chapters 2 and 3 examine what influences police officer discretion when issuing tickets rather than warnings and deciding the amount of fine. Chapter 4 studies police officer discretionary behavior that presents in the duration of stops, search and success rates when drugs/contraband is found, and probability of being ticketed.

Chapter 2 investigates the influence of driver characteristics on police officer discretionary behavior. The study uses data of citations, both written warnings and tickets, for traffic violations recorded by Massachusetts police officers in April and May 2001. In the data, we observe the traffic rule violated by each individual driver. We then collect data on the regulated fine amount that the Massachusetts General Laws suggests for each violation. The variable measuring police officer discretionary behavior is created by subtracting the suggested law amount from the actual fine amount written on traffic citations. We also know the identification number for each individual police officer that wrote a citation. We use police officer fixed effects model to take into account for the unobserved police officer characteristics. The study finds that driver characteristics have economically important effects on police officer discretion. Particularly, police officers are more likely to issue lower fines to female drivers, old drivers, in-town drivers, and in-state drivers than male drivers, middle-aged drivers, out-of-town drivers, and out-of-state drivers, respectively. In addition, the study, using quantile fixed effects, shows that these effects vary across quantiles of the police officer discretion distribution.

Examining decisions within an hour or a day, we show that police officers issue a lower fine and more likely to issue a warning to a driver after issuing a ticket during the previous stop. We also find that although police officers show less discretion at the end of month than earlier times of the month, the difference is minimal. We, therefore, conclude that the conventional wisdom "ticket quota" does not exist.

Chapter 3 explores whether police officer characteristics influence their discretionary decisions. We merge Massachusetts traffic violation records with Boston Police Department data by police officer identification. We have data of all traffic citations written by Boston police officers in April and May 2001. We identify not only driver characteristics but also the race, gender, and working experience of police officers as factors that influence their discretionary decisions. We show that female, black, Asian, or experienced police officers issue fine higher above the suggested fine amount than male, white, or less-experienced police officers, respectively. Next, we examine whether police officers are more lenient toward drivers of their same race. We find that white drivers are treated with the most leniency regardless of police officer race. Black and Hispanic officers show more favor to same race drivers while Asian police officers are strictest compared to other police officers.

Chapter 4 investigates police officer discretionary behavior in stop and search decisions. The study examines not only search and success rates of finding drugs or contraband but also the probability of receiving a ticket as well as the duration of the stop. Using statewide data of all traffic stops in Illinois in 2012, the study finds that police officers are less likely to find drugs or contraband in searches from female and senior drivers compared to searches from male drivers and drivers of other age groups, respectively. This suggests that police officers are stricter toward female drivers and drivers aged older than 51. Using police department fixed effects, we find opposite results. Police officers are more lenient toward both female and older drivers than they are toward male and middle-aged drivers, respectively. Younger drivers aged 16-21 and 21-30 are stopped longer than middle-aged drivers. Moreover, police officers treat white drivers more leniently than drivers of other races in term of probability of issuing tickets, fine, and duration of stop.

In summary, this dissertation shows that driver characteristics such as race, gender, age, and resident status and police officer characteristics such as race, gender, and working experience influence police officer discretionary decisions. Our findings and conclusions have important police implications regarding the management of police officer discretionary decisions since the use of such factors may have ill effects on public trust and undermine the legitimacy of the laws.

This study contributes to the literature on police officer discretion in several ways. It is the first study to examine police officer discretionary behavior in a quantitative way. Second, this study investigates police officer discretionary decisions from various aspects: stopping and searching, issuing tickets, issuing fine amount, and duration of stops. Third, this study allows us to draw conclusions regarding discrimination at the discretion of police officer. Fourth, this study provides an in-depth analysis of factors that might influence police officer discretionary behavior.

Our findings and conclusions have important implications for police departments regarding the management of the discretionary decisions of their officers. It suggests that police officer departments should have more training programs to educate the importance of police officer decisions and actions. Police officers need to understand the outcomes and consequences of their decisions. In addition, the training must be supported by close supervision in order to ensure that desired behaviors. Furthermore, law makers may also wish to publicly establish acceptable limits of discretion in order to guide police officers in the exercise of discretion.

CHAPTER 2

What influences police officer discretionary decisions? Analysis from Massachusetts traffic violation data

2.1 Background

Police officers may exercise their discretion in deciding the appropriate action to be taken regarding violations. Discretion gives police officers flexibility when applying laws to each specific case. A police officer has latitude to decide which driver to pull over, whether to issue a ticket, a written warning or only an oral warning, and the amount of the fine. When talking about police officer discretionary decisions on speeding violations, Harold Chaffin, Police Chief in Tupelo, Mississippi said "Everyone who speeds does not deserve a ticket and everyone who speeds does not deserve to be let go either. We want our officers to have the flexibility to make decisions and use their judgment to handle situations. I cannot make a rule to say everyone stopped gets a ticket. That would not work."[1] That will make us question what influences police officer decisions in issuing tickets and fines.

Besides the fact that police officers should consider the policies, the legislation, and the precedent before making decision, it is important for them to consider each case on its own merits. For the same violation, the penalty can be the same or different due to various factors such as the offense's nature, the offenders' characteristics, and the constitutional laws applicable to the case. The misuse of discretion, however, can lead to abuse of discretionary power and raises public concerns about the legitimacy of police officer discretionary decisions. Therefore, analyzing discretion in police officer decisions is important because of its extensive effects on daily lives of citizens.

[1] "Police discretion called 'cornerstone of justice system"' September 20, 2009 - Daily Journal, Northeast Mississippi News.

To our knowledge, there exist only a few studies focusing on police officer decisions. The majority of the studies examine police officer decisions in issuing tickets versus warnings (Makowsky and Stratmann (2009), Blalock et al. (2011) or stop and search decisions (Knowles et al. (2001), Dharmapala and Ross (2004), Anwar and Fang (2006), and Antonovics and Knight (2009)). In addition, research on police officer discretionary decisions often yields contradictory results. Knowles et al. (2001), Persico and Todd (2008), Grogger and Ridgeway (2006) and Blalock et al. (2011) show that police officers treat drivers equally, regardless of race or gender. In contrast, Dharmapala and Ross (2004), Antonovics and Knight (2009), Quintanar (2011b), and Anwar and Fang (2006) conclude that police officer decisions vary across driver race. Makowsky and Stratmann (2009) and Anbarci and Lee (2014) find that besides driver race, police officers consider other characteristics such as gender, age, and resident status. However, previous research is not able to quantify police officer discretion and focus on police officer decisions of issuing tickets versus warning and searching and stopping.

This study focuses on police officer discretion as measured by the difference between the actual fine amount and the suggested fine amount for that violation. To analyze the determinants of police officer discretionary behavior, we deploy data from the Massachusetts Registry of Motor Vehicles for traffic violations in April and May of 2001. Our final sample consists of 112,674 observations, 50,086 of which are tickets, 62,588 of which are warnings. Figure 2.1 shows the distribution of the difference between the actual fine quoted in citations and the fine suggested in regulation for all traffic citations examined in this study. The difference, ranging from -$575 to $205, shows that police officer decisions vary case by case. Interestingly, there are cases in which real fine amounts are higher than the corresponding amounts suggested in the regulation. For example, considering a failure to stop violation for which the suggested fine is \$50, in the data, fines range from \$0 (only receiving a warning) to \$100, which raises the question of what might influence police officer discretion. Of the 112,674 drivers, only 16,742 (14.86%) are fined at the suggested rates while 71,645 (63.59%) are fined under and 24,287 (21.56%) are fined over the rate listed in the regulation for corresponding violations. Thus, it is important to understand what affects police officer discretionary decisions on traffic violations.

Using a variety of econometric models, we find that driver characteristics influence police officer discretionary decisions. Particularly, police officers issue fine higher to male drivers, out-of-town drivers, and out-of state drivers than female drivers, in-town drivers, and in-state drivers, respectively. White drivers are treated more leniently than drivers of other races including Hispanic, Asian or black. Regarding driver age, police officers are more lenient with old drivers and stricter with young drivers than middle-aged drivers. Police officers are also more lenient with drivers who have a commercial driver license than other drivers. The results are consistent when we consider the full sample with all violations as well as samples with separate traffic violations such as speeding, failure to stop, and lack of inspection sticker. We also show that in-town, in-state, black, female, old, or commercial drivers are less likely to receive a ticket. Moreover, using police officer quantile fixed effect regression proposed by Canay (2011), we examine whether driver characteristics have the same influence over the entire distribution of police officer discretion. We find that police officers treat drivers differently across the fine difference distribution.

In addition, we investigate police officer sequential decisions in order to examine whether police officer decisions on a traffic violation are affected by their previous decisions. Particularly, if a police officer issues a driver a ticket, will he/she be stricter at the next traffic encounter (i.e., issue a ticket rather than a warning or issue a higher fine)? Sequential decisions are considered in two ways: daily or hourly sequences. We find that if a police officer issues a driver a ticket, the police officer will be more lenient at the next traffic encounter in terms of both the likelihood of issuing a ticket and the amount of fine. The conclusion holds when investigating police officer decisions hourly or daily.

We also examine whether police officer discretion is different across time of a month. We show that police officers are stricter with drivers who are pulled over at the end of month than with drivers who are pulled over earlier in the month both in the possibility of issuing a ticket and the fine amount. Although the effects are significant, they are very small compared to the influence of driver characteristics. We conclude that police officer discretionary decisions are not be affected by time of a month. In other words, the rumor " ticket quota" does not exist.

This study contributes to the literature on police officer discretion in several ways. First, it is the first study to examine police officer discretionary behavior in a quantitative way. Police officer discretion is defined as how close the actual fines are to those stated by the law. Since we have data on the fine amounts written on citations and the fine amounts suggested by the Massachusetts General Laws corresponding to their violations, we can quantitatively measure police officer discretion.[2]

Second, this study allows us to draw conclusions regarding discrimination in police officer discretion. While previous research shows evidence that police officers discriminate, the researchers could not conclude if the discrimination was statistical or taste-based. Statistical discrimination happens when police officers use several driver characteristics as a guide to maximize the efficiency of policing. Taste-based discrimination happens when police officers use their own preference to make the

[2] In Massachusetts, police officers have the power to decide both whether to issue a ticket and how much the fine should be for traffic violations. In some states, for example Louisiana, police officers only determine whether to issue ticket. When a ticket is issued, the fine amount will be the same as the one written in the regulation for that violation (Quintanar, 2011).

decisions. While statistical discrimination is allowed, taste-based discrimination is strictly prohibited. In this research, we show that if police officers use their discretion unequally across groups, unlawful taste-based discrimination results.

Third, this study provides an in-depth analysis of factors that might influence police officer discretionary behavior. While a majority of research examine only driver race (Knowles et al. (2001), Persico and Todd (2008), Higgins et al. (2011)) or driver gender (Blalock et al. (2011)), this study investigates several driver characteristics such as race, gender, age, in-town status, in-state status, and commercial driver license possession.

Finally, the study examines not only speeding violations but also other traffic violations such as failure to stop, failure to keep right, and lack of inspection sticker.[3] While there are many studies that focus on police officer discretionary decisions against speeding violations, a few investigate police decisions regarding other traffic violations. Intuitively, police officer decisions should be less discretionary on such traffic violations since violation status is binary. Moreover, there is no degree of severity for those violations. If a driver commits a violation, there will be a specific fine amount for that violation. We discuss how police officer discretion varies across traffic violations.

The remainder of this study is organized as follows. Section 2 reviews the previous literature related to police officer discretionary decisions. Section 3 presents a theoretical model of police officer decision. Section 4 describes the Massachusetts traffic violation data and section 5 presents the econometric models that we use in this paper. Results from analyzing the effect of driver characteristics are presented in section 6 and results from examining police officer sequential decisions and the effect of the end of the month in section 7. Section 8 provides conclusions.

[3] See Table 2.1 for the full list

2.2 Literature review

Most empirical literature on police officer decisions focus on stopping and searching decisions. Knowles et al. (2001) (KPT) argue that if police officers treat drivers equally and the searching cost for each driver is the same, the success rate of finding contraband shall be equal across driver race. They use data of all motor vehicle searches on Interstate 95 in Maryland from January 1995 to January 1999, consisting of 1,590 observations. They find that vehicles of black driver are searched more frequently than the vehicles of white driver (63% versus 29%), but the success rate of finding drugs is equal for both groups. It indicates that police officers treat drivers equally. If the purpose of stopping vehicles is to search for drugs in large amounts, the success rate of finding drugs from black drivers is higher. This implies discrimination against white and Hispanic drivers in favor of black drivers.

However, KPT only examines police officer decisions in searching cars and assumes that the costs of searching drivers of any race are the same across police officers, which is not always true. Moreover, the authors assume that race is the only driver characteristic that influences police officer discrimination. In other words, police officers do not consider other driver characteristics when deciding to search a vehicle. Nevertheless, Blalock et al. (2011), Anbarci and Lee (2014), and Engel and Calnon (2004) show that the decisions of police officer are influenced by other driver characteristics such as gender, age, and resident status as well. In addition, Barbe and Horrace (2012) conclude that the data used in Knowles et al. (2001) cannot provide accurate evidence on racial profiling. They point out that Maryland police officer stop and search decisions were varied and affected by several memoranda signed during that period. There are several research following KPT model to investigate the effect of driver characteristics.

Sanga (2009), using the same model and methodology as in Knowles et al. (2001) but with a larger sample of Maryland drivers from 1995 to 2006, including location fixed effects, reconsiders the findings of Knowles et al. (2001). He shows that black and white drivers are searched at the same rate but Hispanic drivers are searched more frequently. Examining all searches along I-95, he found that police officers discriminate against Hispanic drivers but treat black and white drivers equally. However, when considering all searches by Maryland police officers, he finds that the success rate of finding contraband among white drivers is higher than among black and Hispanics drivers. In other words, there is discrimination against black and Hispanics drivers.

Dharmapala and Ross (2004) generalize the KPT model by taking into account the fact that police officers may not observe all potential offenders. Thus, a fraction of drivers will not be deterred from law violations even if they carry contraband. The authors include two levels of offense severity: carrying a small or a large quantity of drugs. Using the same Interstate 95 data of Maryland from January 1995 to January 1999 as Knowles et al. (2001), they find that how black drivers are treated compared to white drivers depends on the samples and whether drivers choose to carry drugs and contraband. When drivers who carry a small amount of contraband choose to commit with certainty and other drivers randomize between not carrying contraband and carrying large amounts, police officers are more lenient with black drivers. This conclusion holds when considering the full sample, a sub-sample including only male police officers, or a sub-sample including only female police officers. In contrast, when drivers who carry large amounts of contraband will commit with certainty and other drivers randomize between not committing and carrying small amounts, in the sample including only female police officers, the authors find that female police officers discriminate against black drivers.

Anwar and Fang (2006) assume that police officers, before making any decisions on vehicle searches, observe several characteristics of drivers that are correlated with the likelihood that drivers carry drugs. However those characteristics are unknown to drivers. The authors use traffic stop data from the Florida Highway Patrol between January 2000 and November 2001, controlling not only for race but also other characteristics of drivers and police officers that may influence police officer decisions such as age, in-state status, the time when drivers were pulled over, and the rank of police officers. Their insight is that if there is no racial bias, the rates of search and rates of success finding contraband should be independent of driver race and in the same rank order according police officer race. They fail to reject the hypothesis that no racial discrimination exists. But they show that search rates and success rates vary across police officer race.

Alternatively, Antonovics and Knight (2009) assume that driver characteristics that influence police officer decisions are known to both drivers and police officers. The authors argue that if police officers have no racial preference, then the search rates across driver races will be independent of police officer race, given that police officers have the same search costs for drivers of different race. From data on traffic stops in Boston for the two-year period starting in April 2001, they find that police officers are more likely to search the vehicles of drivers whose race is different from theirs. However, the assumption that the cost difference of searching white and black drivers remains the same between white and black officers may not be hold. In addition, the dependent variable is whether police officer conduct a search. Therefore, we only know the difference in probability of being searched among drivers of the same race with other groups.

Police officer decisions on issuing tickets and searching vehicles are different in nature (Anbarci and Lee (2014)). After seeing the pulled-over driver in person and inspecting his/her personal documentation such as a driver license and a vehicle title, the police officer can decide whether or not to search the vehicle. The aim is to make sure that the driver is not carrying contraband. When a police officer stops a driver for that purpose, with reasonable suspicion or legal justification, the police officer can pull over a random car at his/her discretion, even if the driver does not violate any laws. It is, therefore, hard to measure police officer discretion since we do not know and cannot quantify factors that lead a police officer to stop a car and decide to search. However, police officer decisions on traffic violations involve less discretion. A police officer pulls over a driver for traffic violation when the driver violates a traffic rule. Police officers have discretionary power when deciding penalty levels. The literature regarding police officer decisions on traffic violations is limited to issuing a ticket versus a warning and the fine amount.

Blalock et al. (2011) examine traffic stops in five regions of the United States. From pooled data, the authors find no difference in the probability of receiving a ticket between drivers of different races. While investigating each location separately, they show that women are more likely to receive tickets in Bloomington (Illinois), Wichita (Kansas), and the entire state of Tennessee. Men are more likely to be ticketed in Highland Park, Illinois and Boston, Massachusetts.

Makowsky and Stratmann (2009) use data from Massachusetts in April and May of 2001 to investigate what determines the probability that a driver receives a speeding ticket. Their results suggest that besides violations for driving in excess of the speed limit, driver characteristics such as race, gender, and resident status also influence police officers when issuing a ticket. The authors also point out that police officers consider distance between the court house where the ticket can be contested and the house of the driver before making decisions. They argue that if drivers live far from the court house, it is less likely that they will appeal for the tickets. Police officers may consideration that fact when making decisions. However, the study only examines fine amounts for speeding violation and does not include written warnings.

Looking at discrimination from a different perspective, Grogger and Ridgeway (2006) and Quintanar (2011b) examine police officer decisions by comparing the distribution of drivers who were stopped fot speeding violations. Grogger and Ridgeway (2006) compare the distribution of drivers being pulled over at night and day. They argue that if police officers have no racial prejudice, the distribution of the same race drivers who are pulled over at night and day should be identical. Using data collected in Oakland, California, they conclude that there is no racial discrimination in police officer decisions.

Quintanar (2011b) compares the probability of being issued a ticket for a speeding violation by police officers and by automated camera. The data was collected in Lafayette, Louisiana from October 2007 to February 2008. She concludes that African-American and female drivers are more likely to receive a ticket when pulled-over. Quintanar also points out that African-American and female drivers are more likely to receive tickets at day than at night since police officers are more able to detect race and gender during the day. The finding implies that police officers consider gender and race when issuing speeding tickets. However, the sample caught by cameras might not be random, as drivers might notice automated cameras and change their driving behavior before and after passing camera locations. Moreover, since the locations of police officers and automated cameras were different, cameras and police officers investigated different speeding populations, which might lead to various results. Gender and race of drivers caught by automated cameras relied on identification from pictures, which may not be accurate.

Anbarci and Lee (2014) investigate police officer decisions but focus on one different aspect: police officer discretion when providing a speeding discount. Speed discounting occurs when the reported speed is lower than the actual speed. According to Massachusetts laws, individuals who drive 10 or fewer miles per hour over the speed limit are to be ticketed a flat rate of $50. After that, fines rise by $10 for each additional mile over the limit. The authors argue that a police officer will favor a group of drivers if the police officer is more likely to write down the speeding ticket of 10 miles per hour over the speed limit instead of the actual recorded speed (from 11 to 14 miles per hour over the speed limit) for that group. The data includes Boston traffic violations between April 2001 and November 2002 with 14,253 speeding tickets and 1,984 warnings. Using the same model as in Anwar and Fang (2006), they find no racial discrimination. Difference-in-difference model is then used with the dependent variable as the dummy variable of whether or not a driver receives a ticket at 10, conditional on the driver receives ticket and the actual speed between 10 and 14 miles per hour, controlling for other driver characteristics such as gender, age, and resident status and police officer characteristics such as gender, age, work experience.

Their study shows that African-American police officers are stricter than their Hispanic and white counterparts. Hispanic police officers are stricter with Hispanic drivers than with white drivers. African-American police officers are less lenient with white drivers than white police officers are. Moreover, minority police officers are stricter with minority drivers than with white drivers. Male or young police officers are more likely to give speed discounting. In this research, the authors only have data on the reported speed written in citation, not the real speed. They, therefore, assume that all drivers who actually speed at 10 miles per hour over the speed limit will receive only oral warnings instead of citations. And drivers whose speed was written at 10 over the limit were the ones receiving speed discounting from police officers. This may not be true for all cases, however. Using the same data, we can see that some police officers issue tickets to drivers who speed one mile per hour over the speed limit. Therefore, there will likely be many citations in which drivers received no speed discounting and instead were cited at 10 miles per hour over the speed limit.

2.3 Theoretical model

In this section, we present a model to examine if drive characteristics influence police officer discretionary decisions. We assume that police officers are concerned with the total utility which emerges from society and their own utility. Police officers might consider not only violations but also other observable characteristics of drivers. Let $r \in \{b, w, h, a\}$ indicate the race of the driver including black (b), white (w), Hispanic (h), and Asian (a). Driver race is observable by police officers. Let $g \in \{m, f\}$ indicate gender of the driver which is male (m) and female (f). Let c represent other characteristics that are potentially used by police officers in their decision of deciding fine amount such as age, resident status, and time of stops. The value of c may be recorded or partially recorded in the data. Let $d(r, g, c, V)$ represent police officer discretion on traffic violation V.

When a police officer decides to give a discretion d, he tries to maximize the benefit to the society $V(S(d))$ plus his benefit $U(P(d))$. When police officers make the decisions, they care about their benefits. Wilson (1968) shows that police officer administrators determine police officer performance as either "goal-oriented" (e.g. changes in the levels of drug trafficking) or "means-oriented" (e.g. the number of traffic citations issued). Therefore, a police officer will decide on the level of discretion in order to maximize his/her utility:

$$U = U(S(d), P(d)) \tag{2.1}$$

We assume that $P_d > 0$ and $P_{dd} < 0$. To present the trade off between benefits, we add the weight α which represents the marginal rate of substitution between the societal benefit and police officer benefit. Police officer will consider his utility before making decision. His utility function can be written as:

$$U = \alpha U(P(d)) + V(S(d)) \tag{2.2}$$

When $\alpha = 1$, the police officer values his benefit equivalent with the society benefit. When $\alpha < 1$, the police officer values the society benefit higher than his own benefit. When $\alpha > 1$, the police officer undervalues the society benefit relative to his benefit. Police officer will decide the level of discretion d in order to maximize his/her total expected utility. We assume that there is no uncertainty and that the police officer knows the true society benefit and his benefit when he makes the decision. The utility function of police officer benefit can be written as: [4]

$$W(d_w, d_b) = \alpha_w P(d_w) + \alpha_b P(d_b) + S(d_w) + S(d_b) \tag{2.3}$$

Take the first order condition with respect to d_w and d_b, we get:

$$\alpha_w P'_{d_w} + S'_{d_w} = 0 \tag{2.4}$$

$$\alpha_b P'_{d_b} + S'_{d_b} = 0 \tag{2.5}$$

We assume that the marginal benefit from society should be the same when police officers make decisions regarding the violations of black drivers or white drivers ($S'_{d_b} = S'_{d_w}$). From equation 2.4 and 2.5, we have:

$$\frac{\alpha_w}{\alpha_b} = \frac{P'_{d_b}}{P'_{d_w}} \tag{2.6}$$

[4]To illustrate, we consider police officer decisions on traffic violations of two groups of black drivers and white drivers. It can be any groups of drivers

When a police officer does not take into account the race of the driver when making his decisions (i.e. marginal substitution will be the same ($\alpha_w = \alpha_b$)), the marginal benefit from both groups will also be the same ($P'_{d_b} = P'_{d_w}$). That means the police officer will afford the same discretion to both groups (i.e. $d_b = d_w$). If a police officer benefit more when making decisions on the traffic violation of a white driver than that of a black driver ($\alpha_w > \alpha_b$), his marginal benefit with the black driver will be greater than the marginal benefit with the white driver. Since $P'(d)$ is a decreasing function in d, the police officer will yield less discretion on the traffic violation of the black driver (i.e. being stricter with black drivers). If a police officer benefits more from a group of black drivers, he will be more lenient with black drivers.

2.4 Massachusetts traffic violation data

In July 2000, the Massachusetts legislature passed Chapter 228 of the Acts of 2000, "An Act Providing for the Collection of Data Relative to Traffic Stops", which requests to collect information of traffic violations to "identify and eliminate any instances of unlawful racial and gender profiling by police." Accordingly, the Massachusetts Registry of Motor Vehicles required police officers to record race, gender, address and other characteristics of drivers who receive a citation for traffic violation. Police officers also recorded the police agency, the reason, time, and location where a driver was stopped as well as characteristics of the vehicle. For speeding violations, speed over the speed limit and speed zone at which a driver was pulled over were recorded. Table 2.1 presents a summary of all traffic violations examined.[5]

The Massachusetts Registry of Motor Vehicles collected a database of traffic citations in Massachusetts written between April 2001 and January 2003. The Boston

[5]Since we do not have data on the number of times that drivers violate that traffic rule before and the exact location where drivers were pulled over (e.g., bridge, state highways or Massachusetts turnpike), we do not include traffic violations whose suggested fines depend on driving records or locations.

Globe journalists Bill Dedman and Francie Latour obtained data. However, because of lack of funds, data in which both tickets and written warnings were recorded only consists of traffic citations in the months of April and May 2001 .[6] The data set used in this paper is from the period when both tickets and warnings were recorded. The initial data has 166,368 observations, including 82,366 tickets and 84,002 warnings.

We drop several observations for the following reasons. First, we delete 28 duplicate observations. Information about drivers, cars, traffic violations, police officers, and places where vehicles were stopped is the same for 28 pairs. We keep one observation in each pair. Second, we include only white, black, Asian, and Hispanic drivers in our sample. After dropping observations with missing covariates, our final sample includes 112,674 observations, of which 50,086 drivers receive tickets and of which 62,588 drivers receive warnings. For municipality characteristics such as the failure of the override referendum and property values per capita, we do not have data for Boston metropolitan. Therefore, we consider both samples in which we include and exclude Boston in our analysis. Without Boston metropolitan, we have a sample of 99,201 observations including 44,803 tickets and 54,398 warnings.

In addition, we look up Massachusetts General Laws in order to obtain the suggested fine for each traffic violation.[7] The variable "Fine difference" is created by subtracting the suggested fine amount from the actual fine amount that drivers were ticketed. Drivers with warnings do not have to pay any fines. The fine amount is entered as $0 and fine difference will be a negative number, which indicates how lenient police officers are. Table 2.1 reports traffic violations examined in this research with the corresponding regulated fine in General Laws and lists the suggested fine amount as well as the number of cases that are fined over or under the suggested amount.

[6] Dedman and Latour (2003)

[7] There was a change in the regulation of fines for traffic violations during our period of investigation (the end of April 2001). We investigated both versions to find the suggested fine amount.

Besides examining the full sample, we also investigate each traffic violation including speeding, failure to stop, and no inspection sticker. As expected, speeding is the most commonly occurring traffic violation with 78,410 records. Among drivers who are pulled over for speeding violation, 24,133 drivers (30.78%) are fined higher and 50,293 drivers (64.14%) are fined lower than the suggested amount, and only 3,984 drivers (5.08%) are fined at the suggested amount. According to Chapter 90, Section 18, a speeding violation results in a fine of at least $50 for speeding 10 or fewer miles per hour over the speed limit. The fine is then increased by $10 for each mile per hour above this cutoff:

$$Law = 50 + 10 * 1\{Speed > (10 + Speedlimit)\} * (Speed - 10 - Speedlimit) \quad (2.7)$$

From Figure 2.2, most drivers receive tickets for speeding 10 mile per hour (15,747 citations), 15 mile per hour (12,625 citations), and 14 mile per hour (5,381 citations) over the speed limit. More careful investigation of the data reveals that the fines are varied: one individual is issued a ticket for driving 1 mile per hour over the speed limit while another is issued a warning for driving 59 miles per hour over the speed limit.

Figure 2.3 shows the plot of an actual speeding fine by police officers and the fine amount stated in the laws for the speeding violation. The solid line represents the suggested fine amount, which corresponds to number of miles per hour over the speed limit, and the dots represent actual fine amounts issued by police officers. For the same miles per hour over the speed limit, the fine can substantially different from the suggested fine amount. A large portion of drivers receive a warning for speed violation (fine amount equal to 0 in the figure) for which the lowest suggested fine is $50.

We have information about each driver including age, gender, home zip code, in-state and in-town status, and if he/she possesses a commercial drivers license. We also know if the police officer is a state trooper or a local police officer. Regarding violations, we know date and time of day when the driver is pulled over, the violation, and if the driver receive a ticket or a warning and, if any, how much the fine is.

Police officers are also required to report the race and ethnicity of drivers they stop. According to the Massachusetts laws, police officers will "use their best judgment at the time of the citation" to identify race and ethnicity. There are six categories: Asian or Pacific Islander, black, Hispanic, American Indian or Alaskan Native, Middle Eastern or East Indian, and white. In this research, only black, Hispanic, Asian, and white drivers are considered.

We include distance that drivers need to travel to the courthouse in order to appeal police officer decisions. The data lists towns where drivers are stopped, from which we can determine the district court that both police officers and drivers need to show up in case of an appeal. Combined with zip code information where driver's houses locate, we are able to calculate the distance of travel to court house for the driver. For drivers whose distance to the courthouse is less than 5 miles, we input the distance to be equal to 5 miles since it still takes time and effort for drivers to travel to the courthouse.

To control for municipality effects, we include an indicator of whether an override referendum is passed.[8] The override referendum is one part of Proposition 2½, which limits increases in property tax in each Massachusetts municipality. Under Proposition 2½, the total annual property tax in each municipality cannot exceed 2½% of the assessed value of all taxable real and personal properties in that municipality.

[8]The override referendum passing and average property value per capita are obtained from data constructed in Makowsky and Stratmann (2009)

Moreover, the Proposition requires that each municipality can only increase its property taxes by no more than 2½% plus the amount that issues from new properties and new development. If a 2½% increase in taxes plus the amount from new growth is smaller than 2½% of full and fair assessed cash value (levy ceiling), residents in each municipality will have the right to vote to increase the tax amount of that municipality up to the levy ceiling (override referendum). If the override referendum is passed, a municipality can increase its tax rate. Otherwise, a municipality can only increase taxes by 2½% plus new growth. In case the municipality does not have enough revenue for its spending and the override referendum is not passed, it will search for additional revenue from other sources. Funding from traffic violation fines is one of those sources.

In the Massachusetts traffic violation data, for each police officer, there is a unique officer ID coded in order to protect the personal identity. Thus, we are able to use a police officer fixed-effects model to control for time-invariant police officer unobserved characteristics.

2.5 Econometric model of discretionary behavior

First, in this section, we examine if driver characteristics influence police officer discretionary decisions on traffic violations and to what degree. We run OLS regression with police officer fixed effects:

$$Dif_{dpm} = \beta_0 + \beta_1 Driver_{dpm} + \beta_2 Mun_m + \beta_3 Pol_p + \varepsilon_{dpm} \tag{2.8}$$

Dependent variable (Dif_{dpm}) is the difference between the actual and suggested fine amount, which is issued to driver d in municipality m by officer p for a traffic violation.

Mun_m represents the characteristics of municipality m, including an indicator of the existence or rejection of the override referendum in that municipality and a continuous variable of average property tax per capita in municipality where a driver is stopped and fined. Makowsky and Stratmann (2011) show that police officers in municipalities that are tight in budget and issue, on average, higher fine amount. By controlling for override referendum results, we try to eliminate the effect of town budget status on police officer decisions. Since we do not have the financial characteristics of Boston, we consider traffic violations in Massachusetts both including Boston and excluding Boston.

$Driver_d$ includes characteristics of driver d such as dummy variables of whether a driver is black, Asian, or Hispanic (white drivers as the reference group), female, in-town, and in-state driver. It also includes dummy variables indicating driver's age group: 16-21, 22-30, or greater than 51 (drivers aged 31-50 are the reference group), and if a driver has a commercial drivers license. We control for several variables regarding the violation such as if a driver is stopped during the day or at night, and the day of a week. In the data, the time at which a driver pulled over is rounded backward. For example, if a police officer pulls over a driver any time between 4:00 PM and 4:59 PM, the time reported in the traffic citation will be 4:00 PM. Grogger and Ridgeway (2006) find that the distribution of the race of drivers in daytime is different from that in nighttime, possibly because police officers are not able to clearly identify driver race at nighttime. A dummy variable, night, which is equal to 1 if a driver is stopped from 6PM to 5AM and 0 otherwise and an interaction term of whether a driver is black and pulled over at night are created.

We also control for the distance that drivers need to travel to the courthouse in order to appeal police officer decisions. According to Makowsky and Stratmann (2009), police officers might consider their own opportunity cost before making decisions. After the ticket is issued, a driver has two options: pay the ticket or appeal the citation. If he chooses to pay the ticket, the police officer does not need to take any other action; otherwise, the driver can go to court in an attempt to lower or dismiss the fine. In the second scenario, the police officer who issued the ticket must appear in court. As a result, police officers tend to be stricter with drivers who have a higher possibility of paying ticket. The distance information is a proxy for the opportunity cost the police officer may incur if a driver chooses to appeal his citation. For speeding violations, to see the effect of speeding at each speed zone, we include the speed over the speed limit and interaction terms of miles per hour over the speed limit with dummy variables indicating speed zones where drivers were pulled over. These are 15 to 29 mile per hour, 30 to 44 miles per hour, 45 to 54 miles per hour, and 55 to 65 miles per hour zones.

Pol_p indicates unobserved police officer characteristics that are captured by using police officer fixed effects model. Some police officer characteristics might be correlated with driver characteristics and differences in fines. For example, a police officer might be assigned to work in an area with a high density of population whose race is the same as his/her own race. Antonovics and Knight (2009) and Anwar and Fang (2006) show that police officers tend to be more lenient with drivers who are the same race.

In an attempt to shed more light on these issues, we continue our empirical analysis in order to examine what affects police officer decisions in issuing ticket:

$$Ticketed_{dpm} = \beta_0 + \beta_1 Mun_m + \beta_2 Driver_{dpm} + \beta_3 Pol_p + \varepsilon_{dpm} \tag{2.9}$$

The dependent variable $Ticketed_{dpm} = 1$ if police officer p issues a ticket to driver d at municipality m, and is 0 if the police officer issues a warning. Other covariates are the same as in equation 2.8. If $\beta_2 = 0$, it suggests that driver characteristics do not influence police officer decisions on issuing tickets.

We then use the Heckman selection model in order to estimate the effects of driver characteristics on police officer discretionary decisions:

$$Ticketed_{dpm} = \beta_0 + \beta_1 Mun_m + \beta_2 Driver2_{dpm} + \beta_3 Spol_p + \beta_4 CDL_d + \varepsilon_{dpm} \quad (2.10)$$

$$Dif_{dpm} = \beta_0 + \beta_1 Mun_m + \beta_2 Driver2_{dpm} + \beta_3 Spol_p + \varepsilon_{dpm} \quad (2.11)$$

where $Ticketed_{dpm}$, Dif_{dpm}, Mun_m, $Spol_p$ are the same as defined before. $Driver2_d$ includes driver characteristics such as dummy variables indicating a driver is black, Asian, or Hispanic (white drivers are used as the reference group), female, in-town, and in-state driver, and dummy variables for age groups. CDL_d is the dummy variable which indicates if a driver owns a commercial drivers license.

2.6 An analysis of Massachusetts police officer discretionary decisions

Table 2.2 presents the summary statistics of variables used in analysis. Columns 1, 3, and 5 include all traffic violations that were recorded in Massachusetts while columns 2, 4, and 6 exclude the citations written in the Boston metropolitan area. We can see that including or excluding those citations in our sample does not much change the average characteristics of the sample. Columns 1 and 2 present the average values of variables for the full sample. Drivers receive an average of $41.97 below the amount stated in the regulation, the corresponding number is $42.54 (when citations in Boston are excluded). Of the 112,674 total drivers, 29,520 drivers (26.2%) are in-town, 97,463 drivers (86.5%) are in-state, 42,252 drivers (37.5%) are female, and 3,447 drivers (3.06%) own a commercial drivers license. Among pulled-over drivers, the percentage of Black drivers (7.23%) is higher than that of Hispanic drivers (5.08%) and that of Asian drivers (2.86%) and white drivers represent 84.83%. Approximately 33.9% of drivers are stopped at night and 24.6% are written by state police.

The last four columns in Table 2.2 present statistics for a sample of drivers who receive warnings and tickets, separately. Of those who get warnings, 31.2% are in-town drivers and 90.7% are in-state drivers while of those who receive tickets, the numbers are 20% for in-town drivers and 81.1% for in-state drivers. The percentage of black drivers get warnings or tickets are similar: 7.04% and 7.48%, respectively. Meanwhile, Hispanic, Asian and young drivers are more likely to be issued a ticket than a warning (4.05% vs. 6.36% for Hispanics, 2.47% vs. 3.34% for Asian, and 12.8% vs. 17.7% for young drivers). In contrast, 41.9% of female drivers and 18% of old drivers have a chance of receiving warnings while 32.1% of female drivers and 11.8% of old drivers have a chance of receiving tickets.

When investigating police officer decisions, a few studies include drivers who receive warnings when investigating police officer decisions in issuing fines (Makowsky and Stratmann (2009)). However, omitting drivers who receive only warnings is not appropriate since those drivers pay no sum at all for their traffic violations. From the data, on average, each person who receives a warning should have paid \$75.81. In addition, on average, the difference between actual and suggested ticket amounts for drivers is small, \$0.31, police officer discretion in issuing fines may still exist. Figure 2.4 shows that among drivers receiving tickets, a significant number of citations cite fines higher than that suggested by the regulation.

2.6.1 Mean difference of fines, fine difference, and the probability of being ticketed across races, gender, and age groups

Table 2.3 presents the average value of fines and fine difference and the average probability of receiving a ticket across race, gender, or age group in order to check if and how police officers are more lenient with any subgroup of drivers. Columns 2, 4, 6 present the p-value of the t-test that tests if the mean of the differences in fine between two groups is equal to 0, of which the control group is in the first row of each panel. If we only look at fine amounts, we find that white drivers and Asian drivers receive, on average, similar fine amount: $104.69 and $103.62, respectively. Hispanic drivers receive the lowest fine amount of $98.49 and black drivers receive average fine amounts of $99.19. The values may indicate that police officers are stricter with white drivers than drivers of other races and that Hispanic drivers are treated the most lenient. However, when we take into account the severity of violations by looking at the fine difference, white drivers receive the most favor from police officers. On average, white drivers receive fines $43.04 below the amount suggested for violations and have the lowest probability of receiving a ticket compared to drivers of other races. Asian drivers are treated strictest, receiving an average of $21.26 lower than the suggested fine amount, compared with $31.21 for Hispanic drivers and $40.8 for black drivers. Police officers are more likely to issue Hispanic drivers a ticket than drivers of other races.

Police officers are more lenient with female drivers than male drivers regarding fine amount, fine difference, and probability of being ticketed. Female drivers receive an average fine amount of $100.47 which is $47.31 lower than the suggested fine amount. Of all female drivers who were pulled over, 38% are issued tickets while the corresponding number for male drivers is 48%.

When dividing samples by both race and gender, we find that white drivers and Asian drivers regardless of gender receive on average fine amount higher than black drivers and Hispanic drivers. However, we show that police officers are more lenient toward white and black drivers in both fine difference and the probability of receiving a ticket. Although, both male and female Hispanic drivers receive the lowest fine amounts compared to other races, they receive the least favor from police officers when fine difference is considered.

Older drivers are treated with the most leniency compared to drivers from other age groups: an average fine amount of \$98.31, which is \$47.36 lower than the suggested fine amount; their probability of receiving a ticket is 0.34. Younger drivers aged 16 to 21 receive on average the highest fine amount of \$113.59; their probability of receiving a ticket is 0.53.

In general, using only fine amounts to consider police officer decisions may lead to incorrect conclusions. We point out the need to account for the severity of violations into account as well as how police officer decisions deviate from suggested fines in order to have a better understanding of police officer discretion. We also show that police officers are stricter toward Asian drivers and Hispanic drivers than with white drivers and black drivers. In addition, police officers are more lenient with female drivers and old drivers than male drivers and middle-aged drivers, respectively.

2.6.2 Police officer discretionary decisions in issuing fines

Comparing the means only inform us about the difference outcomes between two groups. But we do not know what causes the difference. We use police officer fixed effects models in Equation 2.8 to estimate the effect of drivers characteristics on police officer discretionary decisions. Table 2.4 presents the results from three different samples: receiving either warnings or tickets, receiving warnings, and receiving tickets. Table 2.4a includes driver characteristics and Table 2.4b includes other characteristics. When examining the full sample of 112,674 citations, we find that in-town drivers get an average of \$3.69 lower in fine differences than out-of-town drivers. If a driver resides in-state, he gets an average of \$8.05 lower in fine differences than an out-of-state driver with a comparable violation. These findings are consistent with the hypothesis that drivers outside the municipality have less possibility of appealing the ticket and have no power in the voting system. White drivers, on average, are treated with more leniency than Hispanic drivers (a $7.2 lower in fine difference) and Asian drivers (a $6.7 lower in fine difference), but stricter than black drivers (a $1.5 higher in fine difference). Female drivers receive more favor, a $5.74 lower fine difference, compared to male drivers.

Police officers are stricter toward younger drivers (an average of $4.90 higher in fine difference) and more lenient toward older drivers (an average of $2.89 lower in fine difference) than drivers aged 31 to 50. A report finds that as a driver gets older, he/she is more worried about having a crash and that a driver under 30 tend to pass most drivers.[9] Given the careless driving behaviors of young drivers, police officers may treat young drivers stricter in order to prevent them from violating traffic rules in the future.

The fine difference for drivers who own a commercial drivers license average $7.52 lower than other drivers. Moreover, police officers are more likely to be lenient with drivers who are pulled over at night, showing about $1.91 lower in fine differences than drivers who are pulled over at other times of a day. The sign and significance level of independent variables remain the same when we consider smaller samples such as excluding drivers stopped in Boston in column 2 and including drivers receiving tickets only in column 5.

When examining the sample of drivers who receive only warning in columns 3 and 4, we find again that police officers are stricter toward Hispanic and Asian drivers and more lenient toward drivers who are pulled over at night. State police are stricter than local police. In contrast to previous results, we find that police officers issue fines that average $0.91 higher to old drivers and average $1.80 lower to young drivers compared to drivers aged 31 to 50 years old. Moreover, in-town drivers receive $0.67 higher in

[9] National Survey of Speeding and Unsafe Driving Attitudes and Behaviors 2002 - Final Report - National Highway Traffic Safety Administration, November 2003

fine difference than out-of-town drivers. However, since drivers in this sample only receive warnings, none of them has to pay a fine, we can not conclude that police officers are stricter toward in-town drivers.

Second, we examine police officer discretionary behavior across smaller samples using police officer fixed effects models. Table 2.5 gives summary statistics and Table 2.6 presents the effect of driver characteristics on police officer discretion. Columns 1 and 2 are for the sample of drivers who are pulled over for speeding violations, columns 3 and 4 for failure to stop violations, and columns 5 and 6 for no inspection sticker violations.

From Table 2.5, a driver receives an average fine amount of $45.08 lower than the suggested fine amount for his/her violation. Drivers who fail to stop receive fines that are on average $34.08 lower than the suggested fine amount. Given in the Massachusetts General Laws c90 §1B, the suggested fine amount for a driver who violates the failure to stop rule is $50, $34.08 is a significant amount, which makes us question the efficiency of failure to stop traffic laws. Is the suggested fine so high that police officers decide to lower it in order to make it reasonable? Or do police officers use this violation as a reason to stop drivers for further investigation? The corresponding number for the violation of no inspection sticker is $22.9 lower than the suggested fine amount of $50.

Compared to summary statistics of the whole sample in Table 2.2, the proportions of in-town drivers and in-state drivers in the sample of drivers who are pulled over for speeding violations (23.8% and 84.6%) is smaller than corresponding proportions in the full sample (26.2% and 86.5%). In contrast, police officers are more likely to pull over in-town drivers and in-state drivers for failure to stop (34.6% and 90.6%) or no inspection sticker (29.5% and 94.6%). Black, Hispanic, Asian, and older drivers are less likely to be pulled over for speeding violations. Younger drivers are more likely to be pulled over for failure to stop. For speeding violations, drivers tend to be pulled over at an average of 15.03 miles per hour over the speed limit. Moreover, of all stops due to speeding violations, 10.3% occur in 15-29 mile per hour speed zones, 58.2% in 30-44 mile per hour speed zones, 24.5% in 55-65 mile per hour speed zones, and 7% in 45-54 mile per hour speed zones.

Table 2.6 presents the effect of driver characteristics on police officer discretion for each traffic violation. Table 2.6a shows that when violating speeding rules, an in-town driver receives on average a \$4.71 lower fine difference than an out-of-town driver, the corresponding number for in-state and out-of-state drivers is \$8.94. Police officers are stricter with Hispanic and Asian drivers (\$8.19 and \$7.87 higher in fine difference) than white drivers and more lenient toward black drivers (\$1.87 lower). Police officers give female drivers an average of \$6.78 lower in fine differences than male drivers. Compared to drivers aged 31 to 50, drivers aged 16 to 21 and drivers aged 22 to 30 are treated stricter (\$8.05 and \$4.40 higher) while drivers older than 50 are treated more leniently (\$3.34 lower in fine difference), respectively. Police officers give drivers who have commercial drivers license \$9.32 lower in fine difference than other drivers. These findings are consistent with previous findings when examining the full sample.

The results also show that the higher the speed zone, the stricter police officers are. When a driver is pulled over in a speed zone of 55 to 65 miles per hours, each mile per hour over the speed limit will lead to \$0.73 higher in fine difference compared to a driver who is pulled over in a speed zone of 45 to 54 miles per hour. If a driver is pulled over at 15 to 29 or 30 to 44 miles per hour speed zone, he/she will receive respectively an average of \$1.5 and \$0.8 lower in fine difference compared to a driver pulled over at 45-54 miles per hour speed zone. These findings strengthen the support for the hypothesis that police officers fine higher for more severe violations in order to prevent drivers from violating in the future since speeding in high-speed zone is far more dangerous and can cause worse damage than in slower-speed zones.

We find that the point estimates for the sample of drivers who fail to stop have the same sign and significance level as in previously discussed regressions. The magnitude is smaller in all estimates compared to the estimates for samples of drivers who speed. This suggests that police officers provide less discretion on failure to stop violations. Part of the explanation for the finding is that the suggested fines for speeding violations show wider range than those for failure to stop violations. For the sample of drivers who have no inspection sticker, we find that police officers are more lenient toward in-town drivers, female drivers, and old drivers than out-of-town drivers, male drivers, and middle-aged drivers and stricter with young drivers.

2.6.3 Police officer discretionary decisions on issuing tickets versus warnings

Tables 2.7 examines police officer decisions on issuing tickets to drivers using Equation 2.9 with police officer fixed effects models. These results are consistent with the estimates when considering the full sample in Table 2.6 in terms of sign and levels of statistical significance. These estimates show that police officers are less likely to issue a ticket to in-town, in-state, female, and older drivers while young or Hispanic drivers have higher possibility of receiving a ticket. In addition, police officers are more lenient toward drivers who own a commercial drivers license.

2.6.4 Police officer discretionary decisions - Heckman selection model

Next, we concern that some groups of drivers tend to be treated stricter than other groups but not because police officers make decisions against them. Those groups may drive more carelessly and violate traffic rules more often than other groups. The results therefore may incorrect due to sample selection bias. We conduct a two-step Heckman selection model in order to examine if driver characteristics affect police officer discretionary decisions when issuing fines using Equations 2.10 and 2.11. Makowsky and Stratmann (2011) argue that a police officer is more likely to hesitate when issuing a driver who owns a commercial drivers license a ticket since the ticket may potentially affect the driver's career. However, once a police officer decides to issue a ticket, he shall not treat commercial drivers more leniently than other drivers. Following Makowsky and Stratmann (2011), we assume that possessing a commercial drivers license influences police officer decision when issuing a ticket but is unrelated to police office discretion regarding the fine amount.

Estimates from the two-step Heckman selection models are presented in Table 2.8. Compared to Table 2.4, the coefficients for in-town, in-state, black driver, state police officer, and pulled over at night are the same in sign and significance level when examining the full sample. In-town drivers receive an average of \$1.26 lower in fine differences than out-of-town drivers, compared with \$3.69 when using the fixed effects model. Estimates for Hispanic driver and female driver are not statistically significant, although they have similar magnitudes. In contrast to results listed in Table 2.4, police officers are stricter toward old drivers (\$2.3 higher in fine difference) and more lenient toward young drivers (\$1.9 and \$0.9 lower in fine difference) than middle-aged drivers. These findings represent the opposite of the common perception that police officers often treat older drivers more leniently. Makowsky and Stratmann (2011) use the Heckman selection model with the same data and, looking at sample of speeding drivers, also find that the older drivers are, the lower the fine will be. However, their study includes a logarithm for age and therefore does not divide driver age into age groups.

Columns 3 and 4 in Table 2.8 present the estimates for sample of drivers who are pulled over for speeding violations. The point estimates have the same sign and significance levels as the estimates in the Table 2.6 but in larger magnitude. Columns 5 and 6 are for the sample of drivers failing to stop. The signs of estimates are opposite to the signs of estimate in the Table 2.6. These findings might not be conclusive. In order for the Heckman selection models to be valid, we must assume that the ownership of a commercial driver license will not influence police officer decisions of issuing fines. However, all of our previous results in Tables 2.4 and 2.6 show that drivers who own a commercial drivers license receive, on average, lower fines than other drivers. That makes this assumption invalid and questions the conclusions in Makowsky and Stratmann (2011).

2.6.5 A quantile fixed effect analysis of Massachusetts police officer discretionary decisions

The mean approach, however, does not allow for the heterogeneity effect of driver characteristics across the distribution. To investigate how the effect of driver characteristics varies across the distribution of police officer discretionary decisions, we use a quantile fixed effects model. Canay (2011) proposes the quantile fixed effects model in which he assumes that the unobserved heterogeneity errors have a pure location shift term, assumed to affect all quantiles in the same way, on the conditional quantiles of the dependent variable.

We apply the model into our analysis with the following steps. First, we run the OLS regression with police officer fixed effects in Equation 2.12 in order to obtain the estimated coefficient $\widehat{\beta}$.

$$Dif_{dpm} = \beta Char_{dpm} + \theta_p + \varepsilon_{dpm} \tag{2.12}$$

where $Char_{dpm}$ presents all the characteristics that influence police officer discretion, combining $Driver_d$, $Spol_p$ in Equation 2.8. And θ_p presents all unobserved invariant police officer characteristics. He assumes that $\varepsilon \sim U(0,1)$. After running Equation 2.12, $\widehat{\theta}_p$ and $\widehat{Dif_{dpm}}$ are defined as:

$$\widehat{\theta}_p = E_p[Dif_{dpm} - \widehat{\beta}Char_{dpm}] \tag{2.13}$$

$$\widehat{Dif_{dpm}} = Dif_{dpm} - \widehat{\theta}_p \tag{2.14}$$

Finally, we run quantile regression with bootrapping standard errors of $\widehat{Dif_{dpm}}$ on $Char_{dpm}$ in order to obtain quantile fixed effect estimators. In Figure 2.5, we present a fine difference plot, which shows a deviation from normality.

Table 2.9 presents results for the full sample.[10] We also present the results from the standard mean approach for comparison in column 1.[11] We report the heteroskedasticity robust standard errors fixed effects at police officer level for the OLS estimates and the standard errors based on 100 bootstrapped cluster replication for the fixed effects quantile regression.[12]

In the fixed effects model, in-town drivers receive an average of \$3.69 lower in fine difference than out-of-town drivers. We find the monotonically increasing (in absolute value) influence of in-town status and age over the fine difference distribution. At the upper tail of the distribution, police officers are more lenient with in-town drivers and old drivers. In the 90th percentile, a police officer issues a fine of \$8.46 lower to an in-town driver than to an out-of-town driver and issues a fine of \$5.25 lower to an old driver than to a middle-aged driver while the corresponding numbers in the 10th percentile are \$0.55 and \$1.35. It indicates that those police officers who are very strict when issuing fines are still more lenient with in-town drivers and old

[10]For summary statistics of samples used in analysis, see Table 2.2 and 2.5.
[11]Equation 2.8 presents the model used for mean approach with police officer fixed effects
[12]The results from using quantile fixed effects with sample of drivers pulled over for failure to stop and no inspection sticker violations are presented in Table 2.11 and Table 2.12 for reference

drivers. Over the entire fine difference distribution, we find that police officers are more lenient with in-state drivers, female drivers, and drivers with a commercial drivers license than out-of-state drivers, male drivers, and noncommercial drivers.

We show that police officers are more lenient toward black drivers in the 90th percentile, giving them \$5.83 lower in fine difference compared to white drivers. In contrast, police officers are stricter to Hispanic and Asian drivers across all quantiles of the fine difference distribution. We find that strict police officers tend to show less discretion across drivers of different races compared to more lenient police officers. Young drivers, aged 16 to 21 and 22 to 30, are treated stricter than middle-aged drivers at all quantiles. They need to pay \$10.45 higher in fine difference than drivers 31-50 years old at the 90th percentile while the corresponding number at the 25th percentile is \$1.82. It might be the case that strict police officers issue higher fines to young drivers to prevent them from violating the traffic rules in the future. State police officers are stricter than local police officers at all quantiles. In the 10th, 25th, and 50th percentile, we find that police officers are more lenient to drivers who are pulled over at night, but in the 75th and 90th quantile, we find the opposite results.

We continue presenting the results from using police officer quantile fixed effect regression for sample of drivers who are pulled over for speeding violation (Table 2.10). We find that police officers are more lenient with in-state drivers, female drivers, older drivers, and drivers with a commercial driver license across all quantiles. Hispanic and Asian drivers are treated stricter than white drivers. At the 10th percentile, police officers give black drivers \$3.68 lower than white drivers while the corresponding estimate at the 90th percentile is \$4.89. The pattern, sign, and significance level is mostly the same as those when considering the full sample except for a few points. We find that the discretion toward Asian drivers and white drivers is monotonically decreasing over the distribution of police officer discretion.

We also show that at the lower tail, police officers are more lenient with drivers pulled over for speeding violations and stricter at the upper tail of distribution. At the 10th percentile, for each mile per hour over the speed limit, drivers receive $5.44 lower in fine difference but at the 75th and 90th percentiles, drivers receive $0.94 and $1.37 higher in fine difference. In addition, police officers are more lenient when pulling over drivers in a low speed zone than in a high speed zone over all quantiles of distribution.

2.7 Factors influencing police officer discretionary behavior

2.7.1 An analysis of Massachusetts police officer sequential decisions

In 2007, Rep. Neil Hanse, D-Ogden, has decided to sponsor HB255, a bill that bars police departments from imposing traffic ticket quotas on its officers. Hansen told members of the House Law Enforcement and Criminal Justice Standing Committee about the rumor that Ogden police officers were told to write eight tickets a day. "That comes to about one ticket an hour" he said. In addition, assistant Ogden Police Chief Wayne Tarwater admitted that the city has a performance - based standard which requires at least three citations per week. [13]. If both statements are true, we can expect that after police officers achieve the limit (i.e. one ticket within an hour), he/she may feel relief and behave more leniently in the next encounter. On the other hand, Wilson (1968) shows that police officer administrators determine police officer performance as either "goal-oriented" (e.g. changes in levels of drug trafficking) or "means-oriented" (e.g. the number of traffic citations issued). So if a police officer considers only his performance, he may issue tickets to all drivers that he pulls over.

Knowing the time when each citation was written, we are interested in studying whether police officer discretionary decisions depend on the mood of police officers.

[13] "Ticket quotas targeted", Geoffrey Fattah, Deseret News, Jan 26th, 2007

Particularly, we question if a police officer is more lenient or stricter toward a driver after the police officer has issued a ticket to the previous driver.

Massachusetts police officer sequential decision data

We use Massachusetts traffic violation data in April and May 2001 and perform some data cleaning and coding as followings. First, we delete 28 citations because of duplicated information on age, race, gender, police officer, time and location that they were stopped, type of violation and even the vehicle information. We keep one case in each pairs. Second, we combine citations. In several pairs of observations, information regarding driver, police officer, time, vehicle and location are the same, except for the type of violation. In particular, we find 86 cases in which drivers make two violations but police officers choose only to issue tickets for seat belt violations and choose only to issue warnings for speeding violations. There are 11 cases in which drivers receive two tickets and 8 cases in which drivers receive only two warnings for both speeding and seat belt violations. We also find that 26 drivers commit both speeding and another violation, 11 drivers commit both failure to stop and another violation, and 17 drivers commit two violations. We identify those cases and combine the fine amount, violation, regulated amount for those violations. In total, we combine 159 cases. Third, we do not include citations if police officer IDs are missing or if a police officer files only 1 citation during the studying period.

We create a dummy variable equal to 1 if a police officer has just issued the previously stopped driver a ticket, and zero if it was a warning.[14] The same method is used to create another dummy variable regarding police officer citing decisions in each hour. Since some officers always issue ticket for each traffic violation, and some issue only warnings, we create two variables to represent the strictness of each police officer. The variables are created by dividing the number of tickets by the number of

[14] If it is the first ticket of a police officer in each day, we code as missing

citations that the police officer writes each day (hour). It is important to control for these variables. For example, if a police officer is very strict and tends to issue tickets for any traffic violations and he is assigned to work in a high-density population of black drivers, we might incorrectly conclude that police officers are stricter with black drivers.

Econometrics models

Controlling for all factors that might affect police officer decisions, we test whether a police officer is stricter or more lenient with the following pulled-over driver after he issues a ticket to a driver given that the ticket is written on the same day (hour) by the following equation:

$$Dif_{dpm} = \beta_0 + \beta_1 Mun_m + \beta_2 Driver_{dpm} + \beta_3 Pol_p + \beta_4 Pticket_{dpm} + \varepsilon_{dpm} \tag{2.15}$$

$$Ticketed_{dpm} = \beta_0 + \beta_1 Mun_m + \beta_2 Driver_{dpm} + \beta_3 Spol_p + \beta_4 Pticket_{dpm} + \varepsilon_{dpm} \tag{2.16}$$

Variable $Pticket_{dpm}$ is a dummy variable, equal to 1 if right before a driver d, a police officer p issued a ticket to a driver and it was within one day (hour) period, equal to 0 if a police officer p issued a warning. We also control for all other variables listed in equation 2.8. The dependent variables are either if a driver is ticketed or the fine difference.

An analysis of Massachusetts police officer sequential discretionary decisions

Table 2.13 gives summary statistics of variables used in examining police officer sequential discretionary decisions. We have a sample of 80,742 observations (67,820, if not including Boston metropolitan) if examining police officer decisions in daily basis and 40,439 observations (31,426, excluding Boston) if examining police officer decisions on an hourly basis. The average values of fine difference is almost the same when including and excluding citations in Boston metropolitan in the sample. The average value of all variables in sample of daily sequences and hourly sequences is not not much different from the average value in the full sample in Table 2.2. Considering all police officers who issue at least two citations a day (hour), on average, each police officer issues one ticket out of two citations (police officer strictness is equal to 0.492 and 0.496).

Table 2.14 presents results when examining police officer daily sequential decisions. We show that if the precedent was issued a ticket instead of a warning, the driver gets an average of 15.7 percentage points lower in the probability of being ticketed or an average of \$11.24 lower in term of fine difference. Most of estimates are still the same in sign and significance level as the estimates in Table 2.4. After issuing a ticket, if a police officer pulls over an in-town driver, the driver will receive 3.2 percentage points lower in probability of receiving a ticket or \$2.39 lower in fine difference than out-of-town drivers. Police officers are stricter with Hispanic and Asian drivers than white drivers. If a police officer issues a ticket in previous encounter, an Hispanic driver will receive 5.9 percentage point higher in probability of being ticketed and \$5.82 higher in fine difference than white drivers. The corresponding numbers for Asian drivers are 5.1 percentage point and \$4.43.

Consistent with results from previous sections, we find that old drivers, female drivers, and drivers with a commercial driver license are treated with more leniency. If the previous encounter results in a ticket, female drivers receive 5.1 percentage points lower in probability of receiving a ticket and \$4.61 lower in fine different compared to male driver. Police officers are more lenient toward old drivers and stricter with young drivers.

Table 2.15 presents results when examining police officer hourly sequential decisions. To construct this sample, we include only police officers who issue two or more citations within one hour for at least once over the whole period. We show that if a police officer issues a driver a ticket instead of a warning, the probability that the next encounter will result in a ticket is 46.7 percentage points lower or an average of $33.45 lower in terms of fine difference. Compared with the coefficient estimates in Table 2.14, we find that police officers, after issuing ticket to a driver, are more lenient in the next encounter when considering police officer discretionary decisions on hourly basis. This finding supports the hypothesis that the police officer feel he has accomplished his goal after issuing ticket in the previous encounter; he therefore tends to be more lenient toward the driver. We also show that police officers are more lenient with in-town drivers, in-state drivers, female drivers, older drivers, and drivers owning a commercial driver license. Moreover, police officers are stricter with Hispanic and Asian drivers, young drivers than white drivers and middle-aged drivers.

Generally, we show that after a police officer issues a ticket instead of a warning, he/she tends to be more lenient with the next pulled-over driver. If a police officer has just issued a ticket to a driver, the probability of issuing a ticket for the next encounter is 15.7 percentage points lower or an average of $11.24 lower in term of fine difference. If the previous ticket is within an hour, the probability of being ticketed for a driver is 46.7 percentage point lower or an average of $33.45 lower in term of fine difference. This can be partially explained by police officer mood. After issuing a ticket to a driver, a police officer might feel as though his/her work has been accomplished. He is, therefore, more lenient toward the next encounter.

2.7.2 *Does ticket-quota exist? Evidence from Massachusetts traffic violation data*

We investigate if police officers are stricter at the end of the month. Conventional wisdom indicates that police officers must operate under the pressure of ticket quotas. On August 26, 2008, Nancy Hall, a resident lawyer, was charged with $100 for a failure to stop violation at the corner of State and Summer streets in Portsmouth, New Hampshire.[15] Although Nancy Hall insisted that she was "not in a particular hurry" and 100 percent sure that she made a complete stop, police officer Eric Bentz wrote her a ticket. Defending herself, Nancy argued that Bentz issued her a ticket in order to meet ticket quota or to get the job done. She also provided information that after receiving the ticket, she returned to the intersection and saw Bentz pulled over vehicles every 20 to 25 minutes. The judge finally declared her not guilty and absolved her of the $100 fine. Although Deputy Police Chief Len DiSesa said the department has neither had quotas nor considered having quotas, concern still exists regarding the existence of ticket quota

In addition, Robert Nixon, Director of Government Affairs for the New Jersey State Policemen's Benevolent Association, admitted that "There is this unfortunate belief that at the end of every month, police are going to be giving out tickets to make revenue".[16] Accordingly, if a police officer does not issue as many tickets as he/she is supposed to in the first few weeks of the month, he/she tends to be stricter at the end of month in order to make up for it.

As we know the exact date a citation is written, we create a dummy variable equal to 1 if the citation is written in the last week of the month and equal to 0 if the citation is written at any other time of the month. Controlling for all factors that

[15] "Attorney beats traffic ticket with quota defense" by Elizabeth Dinan, Jan 10, 2009, the Portsmouth Herald.

[16] "Police ticket quotas get warning" USA Today, 20 June 2014

might affect police officer decisions, we test if police officers are stricter at the end of month. To do so we use the models as follows:

$$Dif_{dpm} = \beta_0 + \beta_1 Mun_m + \beta_2 Driver_{dpm} + \beta_3 Pol_p + \beta_4 Emth_{dpm} + \varepsilon_{dpm} \tag{2.17}$$

$$Ticketed_{dpm} = \beta_0 + \beta_1 Mun_m + \beta_2 Driver_{dpm} + \beta_3 Pol_p + \beta_4 Emth_{dpm} + \varepsilon_{dpm} \tag{2.18}$$

The dependent variables Dif_{dpm} is the difference between the real fine amount and the suggested fine amount. $Ticketed_{dpm}$ is a dummy variable indicating a ticket is issued to driver d by police p in municipality m. $Emth_{dpm}$ is a dummy variable indicating whether the citation was written at the end of month. We also control for all other variables listed in Equation 2.8. Tables 2.16, 2.17, and 2.18 present results from regressing fine difference on dummy variable indicating whether a driver is pulled over at the end of month, controlling for other factors that might affect police officer decisions with police officer fixed effects model.[17]

Table 2.16 presents results when considering the full sample of all traffic violations. We show that time of a month when drivers are stopped has minimal effects on police officer decisions. We find that if a driver is stopped at the end of the month, his/her fine difference is, on average, \$0.99 higher than if he/she is stopped at other times of a month. When examining the sample of drivers receiving only warnings or only tickets,we find that drivers are more likely to be charged higher fines at the end of the month but the estimates are not statistically significant. The coefficient estimates of other variables are nearly the same as the estimates in Table 2.4 in terms of magnitude and significance level. It suggests that the time of the month does not influence police officer discretionary decisions.

[17] Summary statistics of variables used in the samples for these analysis are in Table 2.2 and 2.5.

Table 2.17 uses the same method but includes samples of drivers who are pulled over for speeding violations, failure to stop, and no inspection sticker. Of drivers who are stopped for speeding violation, those stopped at the end of month have an average of $1.2 higher in fine difference than those stopped at other times of a month. The corresponding number for those pulled over for failure to stop is $0.93. The coefficients indicating end of the month for the sample of drivers with no inspection sticker violation is still positive but not statistically significant. Since the effects are very minimal, we conclude that the time of the month has little to no influence on police officer discretionary decisions.

Table 2.18 presents OLS regression with police officer fixed-effects in order to examine the probability of being ticketed at the end of month. It shows that being pulled over at the end of the month, a driver has an 0.8 percentage point higher possibility of being issued a ticket than at other times of the month. When looking at the sample of drivers with speeding violation only, the probability is higher but still low, 0.9 percentage points. For samples of drivers who were pulled over for failure to stop and no inspection sticker violation, the coefficients are positive but not significant.

In general, we show that the notion of the "ticket quota" does not exist. Although the coefficients indicating tickets issued at the end of the month is positive and statistically significant, the magnitude is minimal and negligible. It is true when examining the full sample and single violations such as speeding violation and failure to stop.

2.8 Summary

This paper analyzes important behavioral decisions of police officers regarding stopping and searching a vehicle, issuing a ticket or a warning, the timing of the stop, and the fine amount. We show that there are many factors that affect police officer discretionary decisions. First, police officers are more lenient with in-town and in-state drivers than out-of town and out-of-state drivers. Second, Hispanic and Asian drivers are treated stricter than white drivers while black drivers are treated with more leniency than white drivers. Third, female drivers receive more favor from police officers compared to their male counterparts. Fourth, police officers are more lenient with old drivers and stricter with younger drivers than with middle-aged drivers. Fifth, police officers are more likely to be lenient with drivers with a commercial drivers license than with other drivers. Finally, for speeding violations, speeding in high-speed zone leads to a higher probability of receiving a ticket for the driver and a higher fine difference than speeding in lower speed zones. Our results are consistent across multiple econometric analysis and specifications.

In addition, we estimate the effect of driver characteristics across the distribution of police officer discretionary decisions by using the quantile fixed effects model. We show that driver characteristics influence police officer discretion differently across quantiles. Moreover, further investigation shows that if a police officer issues a ticket instead of a warning to a driver within a day or an hour, the police officer tends to be more lenient with the next encounter in both the probability of issuing ticket and the fine amount. The conclusion is true both when examining police officer decisions in hourly or daily contexts. It suggests that police officer decisions also depend on their feelings at that time.

When examining if police officers are stricter at the end of month compared to other time of the month, we find the effect is minimal. We conclude that "ticket quota" does not exist, although estimates are positive and significant. It is true when examining the full sample and single violations such as speeding violation and failure to stop.

One obvious parallel with our research is the current rising public interest in racial issues in America. Our results suggest the presence of discretion and favoritism regarding interactions between police officers and the general public. However, the bigger question is how to reform policies in order to change a current situation where a significant part of the municipal's budgets are derived from fines and asset confiscation. Apart from other studies and general perceptions, blacks are treated with more leniency in our sample, a result that is consistent across multiple sensitivity analysis. While we do not offer a sufficient explanation for that fact, it would provide an interesting future research question.

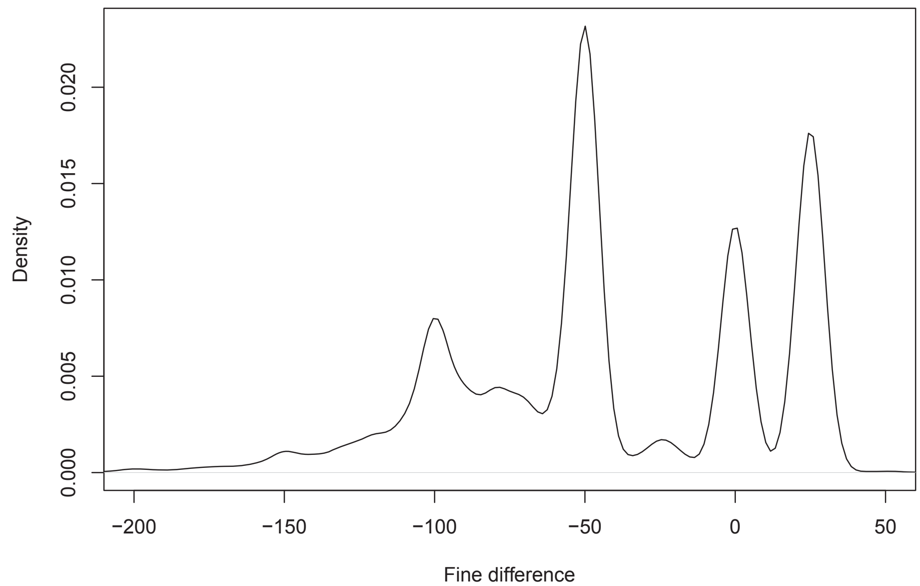

Figure 2.1 *Distribution of the difference between the actual fine quoted in citations and the fine suggested in regulation.*

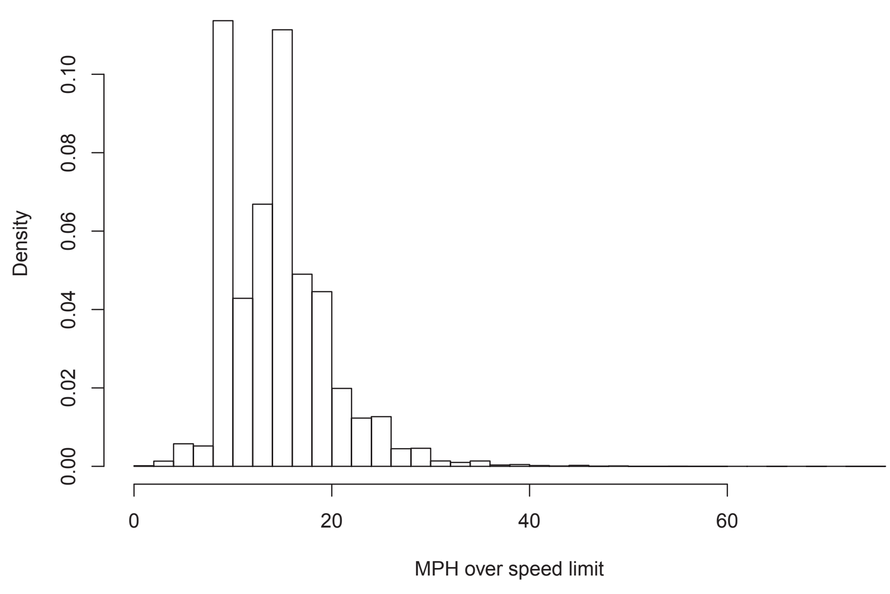

Figure 2.2 *Distribution of speed over the speed limit.*

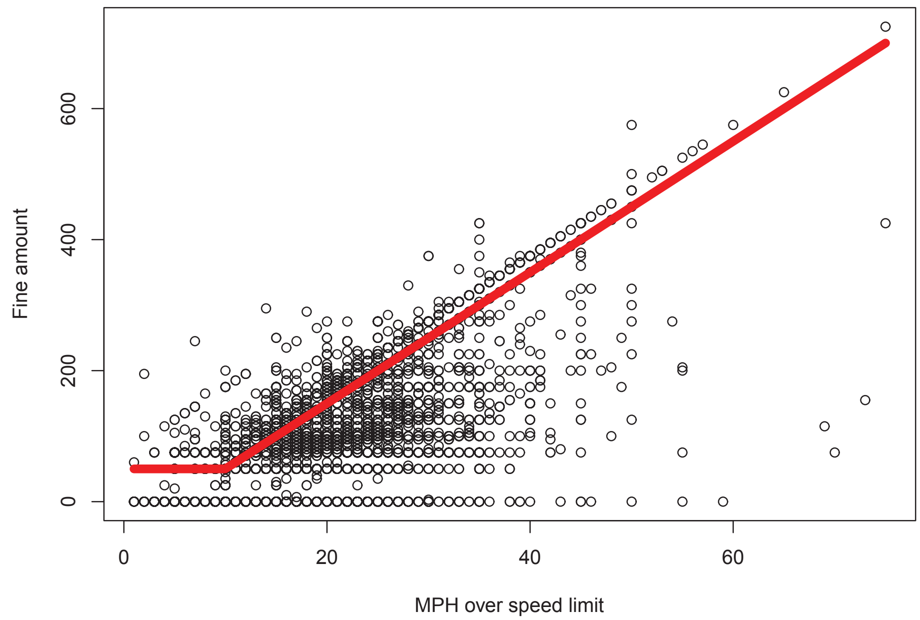

Figure 2.3 *Scatter plot of amount fined by police and amount stated in regulation for speeding violation.*

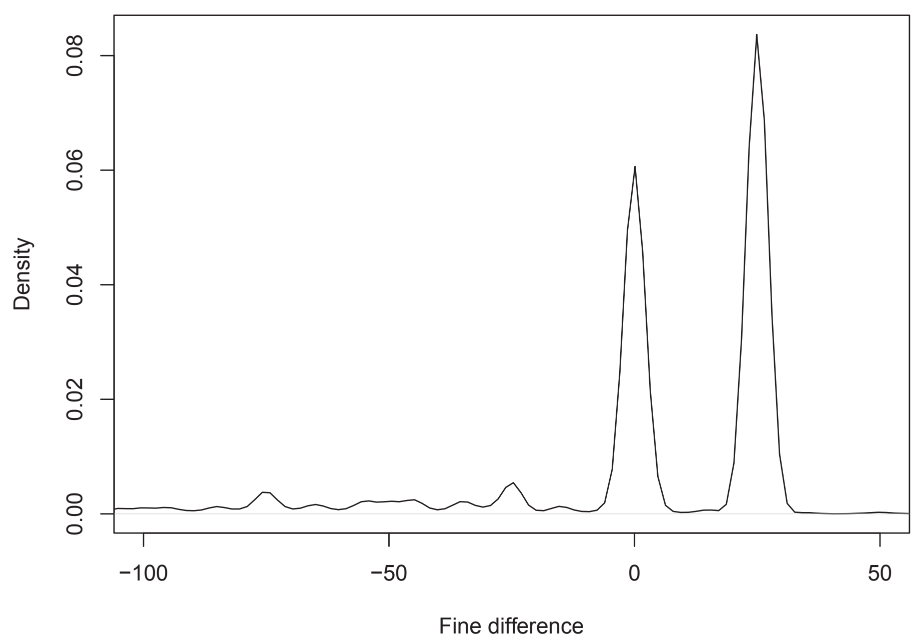

Figure 2.4 *Distribution of the difference between amount that quoted in citation and that in regulation only for drivers who receive tickets.*

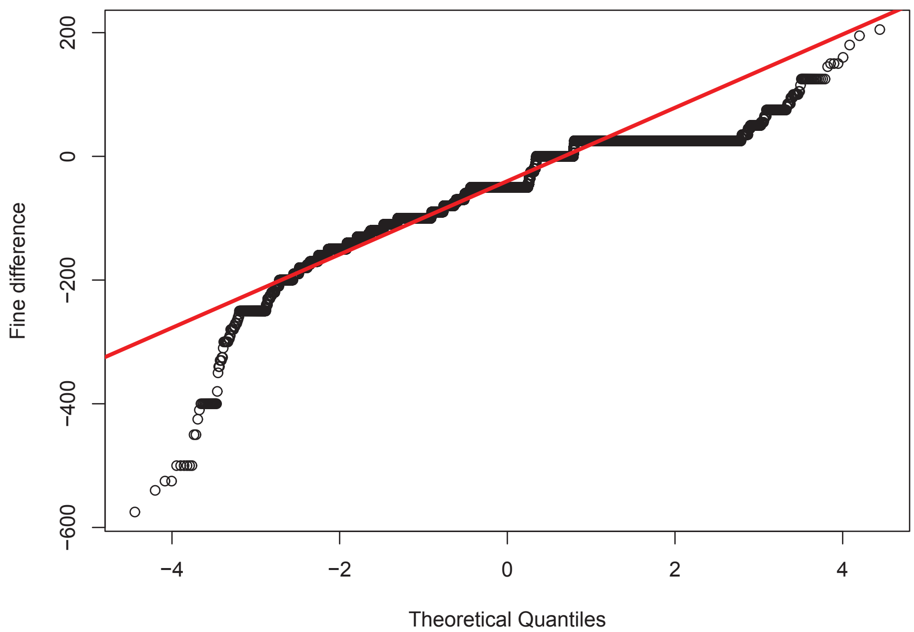

Figure 2.5 *Normal Q-Q plot of fine difference for speeding violations*

Table 2.1 Traffic violations and suggested fines

Violation	Frequency	Regulation fine	Fine under	Fine over	General Laws
Drink open container	62	$500	24	0	c90 §24I
Fail to give signal	281	$25	191	28	c90 §14B
Fail to keep right	72	$100	48	0	c89 §1
Failure to stop	21,532	$50	14,788	24	c90 §1B
Heavy vehicle on municipal way	1	$100	0	1	c85 §30A
Impede emergency vehicle	90	$100	48	0	c89 §7A
Improper passing	660	$100	390	0	c89 §2
Inspection sticker violation	77	$50	34	1	c90 §20
Keep in right lane	1,210	$100	580	0	c89 §4B
Keep right no view	489	$100	299	0	c89 §4
Lane violation	1,767	$100	1,217	1	c89 §4A
Left lane exclusion	63	$100	17	0	c89 §4C
Load no cover/ escape	68	$200	45	0	c85&35
MDC sign/ signal	9	$100	6	0	350 CMR §4.01B
No child restraint	261	$25	72	17	c90 §7AA
No inspection sticker	6,064	$50	2,817	4	c90 §19E
No transparent window	134	$250	101	0	c90 §9D
Oversize vehicle Ns	5	$100	2	0	c90 §19A
Overweight vehicle bridge	6	$200	3	0	c85 §34
Recreation/ Snow violation	7	$100	6	0	323 CMR §3.03
Recreation vehicle unregistered	12	$25	3	0	c90 §21
Speeding	78,410	$50 + $10 * (speed-speed limit-10)	50,293	24,133	c90 §17
State Highway violation	1,293	$20	607	79	720 CMR §9.06
Stop at railroad crossing	18	$200	10	0	c90 §15
Transport unprotected animal	6	$50	5	0	c90 §22H
Trespass with motor vehicle	77	$250	39	0	c266 §121A

This table presents all traffic violations examined in this study together with their frequencies and fine amounts suggested by laws in columns 1 and 2. Columns 3 and 4 are the number of cases that were fined lower or higher than the suggested amount, respectively. Column 5 presents the regulation number in Massachusetts General Laws.

Table 2.2 Summary statistics of variables used in analysis for the whole sample, sample with drivers receiving warnings or tickets only

	All violations		Warnings		Tickets	
Fine difference	-41.97	-42.54	-75.81	-77.83	0.314	0.320
	(52.17)	(53.34)	(33.69)	(34.28)	(38.53)	(39.03)
In-town driver	0.262	0.239	0.312	0.292	0.200	0.175
	(0.440)	(0.427)	(0.463)	(0.455)	(0.400)	(0.380)
In-state driver	0.865	0.858	0.907	0.905	0.811	0.802
	(0.342)	(0.349)	(0.290)	(0.293)	(0.391)	(0.399)
Black driver	0.0723	0.0488	0.0704	0.0454	0.0748	0.0530
	(0.259)	(0.216)	(0.256)	(0.208)	(0.263)	(0.224)
Hispanic driver	0.0508	0.0453	0.0405	0.0346	0.0636	0.0582
	(0.220)	(0.208)	(0.197)	(0.183)	(0.244)	(0.234)
Asian driver	0.0286	0.0254	0.0247	0.0219	0.0334	0.0297
	(0.167)	(0.157)	(0.155)	(0.146)	(0.180)	(0.170)
Female driver	0.375	0.378	0.419	0.424	0.321	0.322
	(0.484)	(0.485)	(0.493)	(0.494)	(0.467)	(0.467)
Age (16-21 years old)	0.150	0.159	0.128	0.137	0.177	0.187
	(0.357)	(0.366)	(0.334)	(0.344)	(0.382)	(0.390)
Age (22-30 years old)	0.259	0.255	0.231	0.225	0.294	0.292
	(0.438)	(0.436)	(0.422)	(0.417)	(0.456)	(0.455)
Age (>50 years old)	0.153	0.150	0.180	0.178	0.118	0.117
	(0.360)	(0.357)	(0.384)	(0.382)	(0.323)	(0.321)
State police	0.246	0.262	0.125	0.130	0.398	0.421
	(0.431)	(0.440)	(0.331)	(0.337)	(0.489)	(0.494)
Commercial license	0.0306	0.0311	0.0353	0.0355	0.0248	0.0257
	(0.172)	(0.174)	(0.185)	(0.185)	(0.155)	(0.158)
Night	0.339	0.348	0.337	0.349	0.342	0.347
	(0.473)	(0.476)	(0.473)	(0.477)	(0.474)	(0.476)
Override fail		0.0171		0.0121		0.0231
		(0.130)		(0.109)		(0.150)
Distance to court		65.26		54.53		78.28
		(287.4)		(269.6)		(307.2)
Property value pc		87,569.6		93,860.6		79,931.4
		(53,058.5)		(53,999.8)		(50,857.9)
Including Boston	Y	N	Y	N	Y	N
Observations	112,674	99,201	62,588	54,398	50,086	44,803

Note: Mean of each variable with standard deviation in parentheses.

This table gives summary statistics of variables used in analysis. Using t-test to compare means of variables between samples in columns 3 and 5; columns 4 and 6 shows that the differences of means in variables (except variable "Pulled over at night") among those receive tickets and warnings are statistically difference from 0.

Table 2.3 The average of fine difference across races, gender, and age groups

	Fine	p-value	Fine difference	p-value	Ticketed	p-value
			By race			
White driver	104.69		-43.04		0.43	
Black driver	99.19	< 0.001	-40.80	< 0.001	0.46	< 0.001
Hispanic driver	98.49	< 0.001	-31.21	< 0.001	0.56	< 0.001
Asian driver	103.62	< 0.001	-32.26	< 0.001	0.52	< 0.001
			By gender			
Female driver	100.47		-47.31		0.38	
Male driver	105.45	< 0.001	-38.76	< 0.001	0.48	< 0.001
			By race for female drivers only			
White driver	101.24		-48.41		0.37	
Black driver	99.98	< 0.001	-42.71	< 0.001	0.41	< 0.001
Hispanic driver	93.01	< 0.001	-34.62	< 0.001	0.50	< 0.001
Asian driver	102.11	0.73	-37.78	< 0.001	0.44	< 0.001
			By race for male drivers only			
White driver	106.41		-39.63		0.47	
Black driver	100.94	< 0.001	-39.86	0.76	0.49	0.06
Hispanic driver	100.11	< 0.001	-30.04	< 0.001	0.58	< 0.001
Asian driver	104.20	0.21	-29.56	< 0.001	0.56	< 0.001
			By age			
Age 31-50	99.75		-44.07		0.42	
Age 16-21	113.59	< 0.001	-38.89	< 0.001	0.53	< 0.001
Age 22-30	105.91	< 0.001	-37.03	< 0.001	0.50	< 0.001
Age >= 51	98.31	0.07	-47.36	< 0.001	0.34	< 0.001

This table gives the mean of fine amount (column 1), fine difference (column 3), probability of being ticketed (column 5). Columns 2, 4, 6 give p-value of the paired t-test with the hypothesis that the difference in mean of two groups is zero.

Table 2.4 The effect of driver characteristics on police officer discretionary decisions of issuing fines for the full sample, sample with drivers receiving tickets or warnings

(a) Driver characteristics

	All violations		Warnings		Tickets	
In-town driver	-3.690***	-4.462***	0.672**	0.569	-1.389***	-1.675***
	(0.334)	(0.653)	(0.272)	(0.485)	(0.468)	(0.590)
In-state driver	-8.052***	-8.660***	0.213	0.711	-6.845***	-7.074***
	(0.424)	(0.627)	(0.429)	(0.718)	(0.461)	(0.519)
Black driver	-1.501**	-2.635***	-0.966	-1.202	-2.553***	-3.458***
	(0.703)	(0.974)	(0.623)	(1.077)	(0.861)	(1.255)
Hispanic driver	7.231***	7.049***	2.241***	0.701	1.219*	1.849**
	(0.644)	(0.895)	(0.625)	(1.328)	(0.727)	(0.808)
Asian driver	6.658***	7.042***	1.768**	2.270***	0.913	1.372
	(0.823)	(0.980)	(0.769)	(0.853)	(0.950)	(1.188)
Female driver	-5.738***	-6.109***	-0.263	-0.428	-0.825**	-1.018**
	(0.284)	(0.394)	(0.245)	(0.305)	(0.363)	(0.448)
Age 16-21	4.902***	5.302***	-1.853***	-1.795***	-1.442***	-1.429**
	(0.413)	(0.575)	(0.381)	(0.461)	(0.489)	(0.651)
Age 22-30	3.624***	3.924***	0.343	0.526	-0.672*	-0.628
	(0.338)	(0.418)	(0.305)	(0.355)	(0.407)	(0.445)
Age >50	-2.885***	-2.632***	0.921***	0.907**	1.521***	1.645***
	(0.402)	(0.467)	(0.329)	(0.396)	(0.551)	(0.512)
Commercial DL	-7.521***	-7.678***	-0.328	-0.731	-3.662***	-3.509**
	(0.791)	(0.947)	(0.648)	(0.808)	(1.083)	(1.397)
Black * Night	1.293	1.550	-0.370	0.485	-0.412	0.016
	(1.107)	(1.578)	(0.997)	(1.604)	(1.336)	(2.123)
Including Boston	Y	N	Y	N	Y	N
Observations	112,674	99,201	62,588	54,398	50,086	44,803

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Other characteristics

	All violations		Warnings		Tickets	
State police	31.270***	36.021***	7.321***	9.636***	2.959	3.373
	(1.369)	(3.856)	(1.325)	(3.614)	(2.224)	(2.664)
Night	-1.905***	-2.143***	-0.920***	-0.947**	-0.849**	-0.850
	(0.342)	(0.612)	(0.300)	(0.472)	(0.430)	(0.603)
Override fail		5.283		-12.659**		3.125*
		(5.864)		(5.607)		(1.729)
Distance to court		-0.001		0.001		0.0003
		(0.001)		(0.001)		(0.001)
Property value pc		<-0.0001		<-0.0001		<0.0001
		(<0.0001)		(<0.0001)		(<0.0001)
Including Boston	Y	N	Y	N	Y	N
Observations	112,674	99,201	62,588	54,398	50,086	44,803

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows results of regressing fine difference on variables (shown in table 2.4a and 2.4b) and controlling for days in the week that drivers were pulled over with police officer fixed-effects and cluster over municipalities.

Table 2.5 Summary statistics of variables for samples of drivers who speed, fail to stop, or have no inspection sticker

	Speeding violation		Failure to stop		No inspection sticker	
Fine difference	-45.08	-45.28	-34.08	-34.36	-22.90	-22.99
	(57.96)	(58.30)	(23.31)	(23.19)	(24.86)	(24.84)
In-town driver	0.238	0.222	0.346	0.310	0.295	0.281
	(0.426)	(0.415)	(0.476)	(0.463)	(0.456)	(0.450)
In-state driver	0.846	0.841	0.906	0.904	0.946	0.944
	(0.361)	(0.366)	(0.292)	(0.295)	(0.227)	(0.229)
Black driver	0.0636	0.0458	0.101	0.0555	0.0658	0.0455
	(0.244)	(0.209)	(0.301)	(0.229)	(0.248)	(0.209)
Hispanic driver	0.0397	0.0360	0.0760	0.0674	0.0811	0.0790
	(0.195)	(0.186)	(0.265)	(0.251)	(0.273)	(0.270)
Asian driver	0.0241	0.0226	0.0457	0.0398	0.0214	0.0170
	(0.153)	(0.149)	(0.209)	(0.195)	(0.145)	(0.129)
Female driver	0.389	0.389	0.371	0.382	0.297	0.296
	(0.487)	(0.488)	(0.483)	(0.486)	(0.457)	(0.457)
Age 16-21	0.164	0.170	0.109	0.126	0.119	0.124
	(0.370)	(0.376)	(0.312)	(0.332)	(0.324)	(0.330)
Age 22-30	0.257	0.254	0.256	0.244	0.313	0.315
	(0.437)	(0.435)	(0.436)	(0.430)	(0.464)	(0.465)
Age >50	0.146	0.145	0.182	0.180	0.114	0.110
	(0.353)	(0.352)	(0.386)	(0.384)	(0.318)	(0.314)
State police	0.289	0.297	0.0529	0.0557	0.227	0.242
	(0.453)	(0.457)	(0.224)	(0.229)	(0.419)	(0.428)
Commercial license	0.0294	0.0297	0.0293	0.0299	0.0368	0.0375
	(0.169)	(0.170)	(0.169)	(0.170)	(0.188)	(0.190)
Night	0.339	0.346	0.367	0.401	0.216	0.210
	(0.474)	(0.476)	(0.482)	(0.490)	(0.412)	(0.407)
Override fail		0.0192		0.00604		0.0282
		(0.137)		(0.0775)		(0.165)
Distance to court		68.75		59.25		50.13
		(291.0)		(292.5)		(272.3)
Property value pc		87,609.4		87,914.3		86,960.7
		(52,622.7)		(47,710.9)		(73,031.3)
Mph over limit	15.03	15.15				
	(5.154)	(5.148)				
Zone 15-29	0.103	0.0983				
	(0.305)	(0.298)				
Zone 30-44	0.582	0.564				
	(0.493)	(0.496)				
Zone 55-65	0.245	0.263				
	(0.430)	(0.440)				
Including Boston	Y	N	Y	N	Y	N
Observations	78,410	72,149	21,532	15,410	6,064	5,467

Note: Mean of each variable with standard deviation in parentheses.

Table 2.6 The effect of driver characteristics on police officer discretionary decisions of issuing fines for samples of drivers who speed, fail to stop, or have no inspection sticker.

(a) Driver characteristics

	Speeding violation		Failure to stop		No inspection sticker	
In-town driver	-4.709***	-5.425***	-0.806**	-1.044*	-1.747**	-1.828**
	(0.429)	(0.830)	(0.322)	(0.606)	(0.705)	(0.832)
In-state driver	-8.944***	-9.080***	-2.318***	-3.591***	-0.050	0.705
	(0.502)	(0.656)	(0.506)	(1.077)	(1.348)	(1.839)
Black driver	-1.872**	-2.798**	0.217	-0.414	-2.869*	-2.648
	(0.925)	(1.101)	(0.630)	(1.103)	(1.472)	(2.222)
Hispanic driver	8.189***	8.437***	3.659***	4.833***	-1.298	-1.455
	(0.883)	(1.192)	(0.565)	(0.845)	(1.179)	(1.411)
Asian driver	7.871***	8.107***	2.108***	1.670*	-1.128	-0.695
	(1.097)	(1.356)	(0.686)	(0.852)	(2.107)	(3.270)
Female driver	-6.784***	-6.892***	-3.006***	-3.083***	-3.026***	-3.001***
	(0.349)	(0.435)	(0.296)	(0.452)	(0.665)	(0.798)
Age 16-21	8.049***	8.229***	2.665***	3.309***	1.233	1.045
	(0.494)	(0.652)	(0.496)	(0.772)	(1.021)	(1.145)
Age 22-30	4.397***	4.431***	1.326***	1.488**	1.250*	1.511*
	(0.420)	(0.511)	(0.351)	(0.578)	(0.703)	(0.912)
Age >50	-3.337***	-3.065***	-3.217***	-2.968***	-4.859***	-4.308***
	(0.504)	(0.598)	(0.390)	(0.605)	(0.974)	(1.153)
Commercial DL	-9.320***	-9.251***	-3.538***	-2.959***	-1.364	-0.602
	(0.995)	(1.024)	(0.851)	(0.985)	(1.628)	(1.915)
Black * Night	1.515	1.668	-0.715	1.505	4.655	2.622
	(1.442)	(1.846)	(1.002)	(2.039)	(3.027)	(5.229)
Including Boston	Y	N	Y	N	Y	N
Observations	78,410	72,149	21,532	15,410	6,064	5,467

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows results of regressing fine difference on variables (shown in table 2.6a and 2.6b) and controlling for days in the week that drivers were pulled over with police officer fixed-effects and cluster over municipalities.

(b) Other characteristics

	Speeding violation		Failure to stop		No inspection sticker	
State police	29.881***	30.332***	2.780	14.609***	2.376	3.962
	(2.023)	(4.626)	(1.844)	(4.064)	(4.111)	(5.639)
Night	-2.137***	-2.216***	-0.199	-0.340	-0.529	-0.502
	(0.427)	(0.722)	(0.374)	(0.511)	(0.863)	(0.956)
Mph over limit	-1.673***	-1.658***				
	(0.055)	(0.184)				
Mphol * z15-29	-1.466***	-1.439***				
	(0.058)	(0.161)				
Mphol * z30-44	-0.795***	-0.780***				
	(0.048)	(0.137)				
Mphol * z55-65	0.728***	0.784***				
	(0.054)	(0.176)				
Override fail		5.058		8.843**		0.977
		(5.491)		(3.457)		(5.707)
Distance to court		-0.0002		-0.001		0.001
		(0.008)		(0.001)		(0.002)
Property value pc		<-0.0001*		<-0.0001***		<-0.0001*
		(<0.0001)		(<0.0001)		(<0.0001)
Including Boston	Y	N	Y	N	Y	N
Observations	78,410	72,149	21,532	15,410	6,064	5,467

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows results of regressing fine difference on variables (shown in table 2.6a and 2.6b) and controlling for days in the week that drivers were pulled over with police officer fixed-effects and cluster over municipalities.

Table 2.7 The effect of driver characteristics on police officer discretionary decisions of issuing a ticket

(a) Driver characteristics

	All violations		Speeding violation		Failure to stop	
In-town driver	-0.049***	-0.057***	-0.053***	-0.060***	-0.017***	-0.022*
	(0.003)	(0.006)	(0.003)	(0.007)	(0.006)	(0.013)
In-state driver	-0.054***	-0.060***	-0.055***	-0.057***	-0.045***	-0.070***
	(0.004)	(0.005)	(0.004)	(0.006)	(0.010)	(0.021)
Black driver	0.005	-0.003	-0.005	-0.012	0.003	-0.012
	(0.006)	(0.008)	(0.007)	(0.008)	(0.013)	(0.023)
Hispanic driver	0.078***	0.079***	0.062***	0.060***	0.075***	0.099***
	(0.006)	(0.009)	(0.007)	(0.011)	(0.011)	(0.017)
Asian driver	0.067***	0.066***	0.059***	0.059***	0.043***	0.035**
	(0.007)	(0.010)	(0.009)	(0.011)	(0.014)	(0.017)
Female driver	-0.070***	-0.070***	-0.055***	-0.055***	-0.061***	-0.063***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.006)	(0.009)
Age 16-21	0.087***	0.091***	0.071***	0.072***	0.054***	0.067***
	(0.004)	(0.005)	(0.004)	(0.005)	(0.010)	(0.016)
Age 22-30	0.051***	0.053***	0.042***	0.042***	0.028***	0.032***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.007)	(0.011)
Age >50	-0.057***	-0.052***	-0.041***	-0.039***	-0.065***	-0.060***
	(0.004)	(0.005)	(0.004)	(0.005)	(0.008)	(0.012)
Commercial DL	-0.081***	-0.078***	-0.085***	-0.083***	-0.070***	-0.058***
	(0.007)	(0.009)	(0.008)	(0.009)	(0.017)	(0.020)
Black * Night	0.020*	0.019	0.009	0.004	-0.015	0.031
	(0.010)	(0.012)	(0.012)	(0.012)	(0.020)	(0.041)
Including Boston	Y	N	Y	N	Y	N
Observations	112,674	99,201	78,410	72,149	21,532	15,410

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows results of regressing dummy variable whether driver was ticketed on variables (shown in table 2.7a and 2.7b) and controlling for days in the week with police officer fixed-effects and cluster over municipalities.

(b) Other characteristics

	All violations		Speeding violation		Failure to stop	
State police	0.332***	0.385***	0.386***	0.392***	0.053	0.287***
	(0.012)	(0.038)	(0.016)	(0.044)	(0.037)	(0.082)
Night	-0.012***	-0.015***	-0.021***	-0.022***	-0.004	-0.006
	(0.003)	(0.005)	(0.003)	(0.006)	(0.008)	(0.011)
Mph over limit			0.029***	0.029***		
			(0.0004)	(0.002)		
Mphol * z15-29			-0.005***	-0.006***		
			(0.0005)	(0.001)		
Mphol * z30-44			-0.002***	-0.002**		
			(0.0004)	(0.001)		
Mphol * z55-65			$<$0.0001	$<$0.0001		
			(0.0004)	(0.002)		
Override fail		0.110**		0.075		0.177**
		(0.049)		(0.047)		(0.069)
Distance to court		-0.0001**		$<$-0.0001*		$<$-0.0001
		($<$0.0001)		($<$0.0001)		($<$0.0001)
Property value pc		$<$-0.0001***		$<$-0.0001***		$<$-0.0001***
		($<$0.0001)		($<$0.0001)		($<$0.0001)
Including Boston	Y	N	Y	N	Y	N
Observations	112,674	99,201	78,410	72,149	21,532	15,410

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows results of regressing dummy variable whether driver was ticketed on variables (shown in table 2.7a and 2.7b) and controlling for days in the week with police officer fixed-effects and cluster over municipalities. (Mphol is miles per hour over the speed limit)

Table 2.8 The effect of driver characteristics on police officer discretionary decisions of issuing fines. Two-step Heckman model

(a) Driver characteristics

	All violations		Speeding violation		Failure to stop	
In-town driver	-1.263***	-1.702**	-8.123***	-10.393***	0.448***	-0.001
	(0.477)	(0.707)	(0.640)	(1.878)	(0.153)	(0.428)
In-state driver	-8.194***	-8.194***	-14.736***	-14.692***	0.811***	-0.922***
	(0.499)	(0.766)	(0.639)	(1.323)	(0.222)	(0.312)
Black driver	-2.718***	-4.558***	0.543	-2.505	-0.176	0.519
	(0.849)	(1.432)	(1.247)	(1.875)	(0.285)	(0.668)
Hispanic driver	0.814	1.097	13.153***	11.933***	-1.318***	0.571
	(0.751)	(0.893)	(1.139)	(1.950)	(0.236)	(0.422)
Asian driver	1.547	1.414	8.888***	9.464***	-0.816***	-0.146
	(0.966)	(1.175)	(1.465)	(2.089)	(0.308)	(0.433)
Female driver	-0.524	-0.904*	-8.470***	-8.744***	0.815***	-0.407
	(0.403)	(0.479)	(0.504)	(0.750)	(0.145)	(0.325)
Age 16-21	-1.870***	-1.813***	9.302***	9.223***	-0.896***	0.615*
	(0.538)	(0.663)	(0.680)	(1.144)	(0.217)	(0.369)
Age 22-30	-0.880**	-0.798*	5.292***	5.243***	-0.600***	-0.175
	(0.434)	(0.464)	(0.588)	(0.826)	(0.165)	(0.408)
Age >50	2.313***	2.429***	-2.655***	-2.124**	0.818***	-0.482*
	(0.584)	(0.594)	(0.767)	(1.076)	(0.206)	(0.261)
Black * Night	0.344	0.489	4.078**	0.807	0.027	-0.190
	(1.330)	(2.248)	(1.948)	(2.768)	(0.451)	(0.652)
Including Boston	Y	N	Y	N	Y	N
Observations	112,674	99,201	78,410	72,149	21,532	15,410

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows results of two step Heckman procedure, regressing fine difference on variables (shown in table 2.8a and 2.8b) and controlling for days in the week.

(b) Other characteristics

	All violations		Speeding violation		Failure to stop	
State police	4.531***	4.793***	22.438***	21.394***	-1.170***	1.685***
	(0.731)	(1.633)	(0.815)	(4.666)	(0.266)	(0.533)
Night	-2.642***	-2.515***	-2.863***	-2.867**	0.172	0.028
	(0.385)	(0.691)	(0.532)	(1.297)	(0.152)	(0.169)
Mph over limit			-1.237***	-1.147***		
			(0.063)	(0.332)		
Mphol * z15-29			-1.061***	-1.019***		
			(0.069)	(0.309)		
Mphol * z30-44			-0.593***	-0.589**		
			(0.055)	(0.252)		
Mphol * z55-65			0.657***	0.651**		
			(0.058)	(0.308)		
Override fail		5.467**		21.920***		2.477***
		(2.613)		(6.276)		(0.764)
Distance to court		0.001		0.0001		-0.0005
		(0.001)		(0.001)		(0.0004)
Property value pc		<-0.0001		-0.000***		<-0.0001***
		(0.0006)		(<0.0001)		(<0.0001)
Including Boston	Y	N	Y	N	Y	N
Observations	112,674	99,201	78,410	72,149	21,532	15,410

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows results of two step Heckman procedure, regressing fine difference on variables (shown in table 2.8a and 2.8b) and controlling for days in the week.

Table 2.9 The effect of driver characteristics over fine difference distribution, full sample

(a) Driver characteristics

	Conditional mean	Q10	Q25	Q50	Q75	Q90
In-town driver	-3.690***	-0.549	-0.905**	-3.034***	-6.610***	-8.457***
	(0.334)	(0.621)	(0.619)	(0.414)	(0.703)	(0.682)
In-state driver	-8.052***	-7.816***	-10.181***	-6.254***	-6.556***	-6.116***
	(0.424)	(1.015)	(1.170)	(0.779)	(0.868)	(0.865)
Black driver	-1.501**	-1.007	0.814	-0.186	-1.425	-5.826***
	(0.703)	(1.999)	(1.437)	(0.760)	(0.961)	(1.127)
Hispanic driver	7.231***	8.924***	10.910***	7.981***	7.627***	2.606**
	(0.644)	(1.769)	(1.290)	(0.852)	(1.156)	(1.059)
Asian driver	6.658***	11.508***	10.764***	5.741***	3.220***	1.059
	(0.823)	(1.199)	(1.059)	(0.676)	(0.989)	(1.110)
Female driver	-5.738***	-3.083***	-5.601***	-4.902***	-7.237***	-7.331***
	(0.284)	(0.561)	(0.587)	(0.372)	(0.525)	(0.651)
Age 16-21	4.902***	-1.061	1.817***	4.666***	9.532***	10.448***
	(0.413)	(0.783)	(0.671)	(0.487)	(0.643)	(0.661)
Age 22-30	3.624***	2.891***	4.364***	3.081***	4.663***	3.731***
	(0.338)	(0.666)	(0.521)	(0.346)	(0.555)	(0.539)
Age >50	-2.885***	-1.353*	-2.112***	-2.230***	-4.345***	-5.250***
	(0.402)	(0.739)	(0.574)	(0.341)	(0.499)	(0.556)
Commercial DL	-7.521***	-6.552***	-8.583***	-6.703***	-7.809***	-5.267***
	(0.791)	(1.589)	(1.168)	(0.828)	(1.082)	(1.158)
Black * Night	1.293	0.808	2.779	0.836	1.181	3.222**
	(1.107)	(2.944)	(2.432)	(1.172)	(1.643)	(1.560)
Observations	112,674	112,674	112,674	112,674	112,674	112,674

Standard errors in parentheses- Bootstraps 100 reps; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Other characteristics

	Conditional mean	Q10	Q25	Q50	Q75	Q90
State police	31.270***	27.284***	34.811***	40.185***	32.133***	20.416***
	(1.369)	(5.054)	(4.935)	(4.807)	(4.724)	(4.461)
Night	-1.905***	-6.572***	-4.714***	-1.362**	1.619**	2.461***
	(0.342)	(1.061)	(0.767)	(0.589)	(0.763)	(0.894)
Observations	112,674	112,674	112,674	112,674	112,674	112,674

Standard errors in parentheses- Bootstraps 100 reps; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows results of quantile fixed effects regressions of fine difference on variables (shown in table 2.9a and 2.9b) and controlling for days in the week that drivers were pulled over.

Table 2.10 The effect of driver characteristics over fine difference distribution, sample with drivers pulled over for speeding violation

(a) Driver characteristics

	Conditional mean	Q10	Q25	Q50	Q75	Q90
In-town driver	-4.709***	-1.087	-1.073	-3.412***	-6.519***	-11.202***
	(0.429)	(0.746)	(0.666)	(0.529)	(0.856)	(1.243)
In-state driver	-8.944***	-7.245***	-10.530***	-5.013***	-6.287***	-5.490***
	(0.502)	(1.033)	(0.961)	(0.715)	(0.986)	(0.808)
Black driver	-1.872**	-3.681*	-0.051	1.231	0.807	-4.890***
	(0.925)	(2.031)	(2.766)	(0.948)	(1.316)	(1.795)
Hispanic driver	8.189***	1.396	5.725***	9.633***	9.081***	4.256***
	(0.883)	(1.709)	(1.512)	(1.348)	(1.407)	(1.543)
Asian driver	7.871***	6.963***	7.152***	6.417***	6.668***	5.249***
	(1.097)	(1.710)	(1.402)	(0.974)	(1.247)	(2.074)
Female driver	-6.784***	-3.441***	-4.532***	-4.172***	-6.377***	-7.746***
	(0.349)	(0.564)	(0.470)	(0.430)	(0.573)	(0.938)
Age 16-21	8.049***	4.788***	4.823***	5.420***	8.585***	10.516***
	(0.494)	(0.645)	(0.726)	(0.571)	(0.945)	(1.022)
Age 22-30	4.397***	2.948***	3.337***	3.377***	4.124***	4.082***
	(0.420)	(0.563)	(0.530)	(0.403)	(0.594)	(0.728)
Age >50	-3.337***	-3.734***	-3.433***	-1.783***	-2.590***	-5.092***
	(0.504)	(0.645)	(0.588)	(0.446)	(0.617)	(0.875)
Commercial DL	-9.320***	-6.684***	-7.964***	-7.595***	-7.880***	-9.564***
	(0.995)	(1.048)	(1.191)	(0.996)	(1.018)	(1.834)
Black * Night	1.515	0.175	-2.754	0.365	0.044	1.666
	(1.442)	(2.388)	(2.491)	(1.348)	(2.062)	(2.593)
Observations	78,410	78,410	78,410	78,410	78,410	78,410

Standard errors in parentheses- 100 bootstraps; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows results of quantile fixed effects regressions of fine difference on variables (shown in table) and controlling for days in the week that drivers were pulled over for speeding violation. Column 1 is results from police officer fixed effects regression. Columns 2 to 6 are results from quantile FE regression with quantile 0.1, 0.25, 0.5, 0.75, and 0.9, respectively.

(b) Other characteristics

	Conditional mean	Q10	Q25	Q50	Q75	Q90
Night	-2.137***	-3.514***	-4.850***	-2.480***	-0.299	2.640**
	(0.427)	(0.836)	(0.878)	(0.767)	(1.114)	(1.292)
State police	29.881***	17.159***	24.502***	28.599***	36.658***	26.973***
	(2.023)	(5.421)	(5.618)	(5.535)	(5.632)	(5.510)
Mph over limit	-1.673***	-5.436***	-4.469***	-1.606***	0.943***	1.365***
	(0.055)	(0.196)	(0.218)	(0.224)	(0.199)	(0.188)
Mphol * z15-29	-1.466***	-1.058***	-1.164***	-1.799***	-1.620***	-0.652***
	(0.058)	(0.112)	(0.135)	(0.213)	(0.253)	(0.158)
Mphol * z30-44	-0.795***	-0.351***	-0.534***	-1.159***	-1.093***	-0.461***
	(0.048)	(0.093)	(0.112)	(0.197)	(0.231)	(0.116)
Mphol * z55-65	0.728***	1.443***	1.952***	1.464***	-0.324*	-0.415***
	(0.054)	(0.136)	(0.206)	(0.217)	(0.198)	(0.135)
Observations	78,410	78,410	78,410	78,410	78,410	78,410

Standard errors in parentheses- 100 bootstraps; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows results of quantile fixed effects regressions of fine difference on variables (shown in table) and controlling for days in the week that drivers were pulled over for speeding violation. Column 1 is results from police officer fixed effects regression. Columns 2 to 6 are results from quantile FE regression with quantile 0.1, 0.25, 0.5, 0.75, and 0.9 respectively. Mphol = mile per hour over the speed limit.

Table 2.11 The effect of driver characteristics over fine difference distribution, sample with drivers pulled over for failure to stop violation

(a) Driver characteristics

	Conditional mean	Q10	Q25	Q50	Q75	Q90
In-town driver	-0.806**	-0.909**	0.045	-0.290***	-0.912**	-2.055***
	(0.322)	(0.406)	(0.355)	(0.090)	(0.388)	(0.574)
In-state driver	-2.318***	0.432	-0.888	-1.466***	-7.222***	-3.118***
	(0.506)	(1.040)	(0.780)	(0.429)	(2.049)	(1.089)
Black driver	0.217	-2.368***	-0.619	0.215	3.814*	-0.057
	(0.630)	(1.682)	(1.044)	(0.520)	(1.966)	(1.389)
Hispanic driver	3.659***	0.741	2.504***	2.004***	11.618***	3.140**
	(0.565)	(1.204)	(0.783)	(0.452)	(2.179)	(1.244)
Asian driver	2.108***	1.955	2.414**	1.228***	7.288***	-0.666
	(0.686)	(1.414)	(1.004)	(0.396)	(2.137)	(1.570)
Female driver	-3.006***	-1.691***	-2.341***	-1.570***	-3.504***	-4.374***
	(0.296)	(0.584)	(0.515)	(0.256)	(0.933)	(0.855)
Age 16-21	2.665***	0.986	1.849**	1.712***	7.019***	2.371***
	(0.496)	(0.776)	(0.717)	(0.354)	(1.669)	(0.827)
Age 22-30	1.326***	0.481	0.896**	0.656***	3.785***	1.511**
	(0.351)	(0.536)	(0.401)	(0.197)	(1.200)	(0.670)
Age >50	-3.217***	-3.340***	-2.693***	-1.854***	-2.206**	-5.074***
	(0.390)	(0.799)	(0.673)	(0.331)	(0.746)	(1.174)
Commercial DL	-3.538***	-2.193*	-3.250***	-2.089***	-3.106***	-4.493**
	(0.851)	(1.225)	(0.887)	(0.718)	(1.017)	(1.860)
Black * Night	-0.715	-0.025	0.590	-0.366	-3.233	-1.450
	(1.002)	(2.040)	(1.294)	(0.765)	(2.766)	(2.499)
Observations	21,532	21,532	21,532	21,532	21,532	21,532

Standard errors in parentheses- Bootstraps 100 reps; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Other characteristics

	Conditional mean	Q10	Q25	Q50	Q75	Q90
State police officer	2.780	5.853***	4.865***	3.268***	0.991	-0.931
	(1.844)	(4.413)	(3.850)	(3.787)	(4.154)	(4.687)
Night	-0.199	-0.850**	-0.557	0.027	-0.629	0.979*
	(0.374)	(0.861)	(0.726)	(0.718)	(0.843)	(0.850)
Observations	21,532	21,532	21,532	21,532	21,532	21,532

Standard errors in parentheses- Bootstraps 100 reps; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows results of quantile fixed effects regressions of fine difference on variables (shown in table) and controlling for days in the week that drivers were pulled over for failure to stop. Column 1 is results from police officer fixed effect regression. Columns 2 to 6 are results from quantile regression with quantile 0.1, 0.25, 0.5, 0.75, and 0.9 respectively.

Table 2.12 The effect of driver characteristics over fine difference distribution, sample with drivers pulled over for no inspection sticker violation

(a) Driver characteristics

	Conditional mean	Q10	Q25	Q50	Q75	Q90
In-town driver	-1.747**	-0.664	-2.002*	-1.691***	-3.529***	-1.162
	(0.705)	(0.992)	(1.372)	(0.562)	(1.136)	(1.025)
In-state driver	-0.050	-2.075	0.531	0.354	2.154	-2.704
	(1.348)	(2.041)	(2.879)	(1.045)	(2.736)	(2.213)
Black driver	-2.869*	-3.230	-0.430	-2.550*	-3.388	-4.153
	(1.472)	(2.449)	(2.588)	(1.465)	(2.147)	(2.723)
Hispanic driver	-1.298	-1.834	-2.437	-0.958	0.013	-2.648
	(1.179)	(1.605)	(2.609)	(1.091)	(1.432)	(2.133)
Asian driver	-1.128	-1.715	0.630	-0.788	-2.037	-4.905*
	(2.107)	(4.613)	(4.189)	(1.869)	(2.732)	(2.803)
Female driver	-3.026***	-2.546***	-4.421***	-2.622***	-3.736***	-2.604**
	(0.665)	(0.928)	(1.304)	(0.621)	(1.168)	(1.048)
Age 16-21	1.233	2.392	1.649	1.177	0.379	0.149
	(1.021)	(1.506)	(1.842)	(0.941)	(1.674)	(2.353)
Age 22-30	1.250*	1.651	1.510	1.194*	1.689	0.936
	(0.703)	(1.158)	(1.203)	(0.644)	(1.033)	(1.016)
Age >50	-4.859***	-5.760***	-8.875***	-3.613***	-4.297***	-3.896***
	(0.974)	(1.288)	(1.915)	(0.997)	(1.623)	(1.438)
Commercial DL	-1.364	2.856	-2.015	-1.080	-3.529	-1.223
	(1.628)	(2.402)	(2.370)	(1.270)	(2.475)	(2.183)
Black * Night	4.655	7.354	6.407*	4.312*	4.711	2.391
	(3.027)	(5.143)	(3.554)	(2.564)	(3.754)	(4.398)
Observations	6,064	6,064	6,064	6,064	6,064	6,064

Standard errors in parentheses- Bootstraps 100 reps; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Other characteristics

	Conditional mean	Q10	Q25	Q50	Q75	Q90
State police officer	2.376	2.717***	2.548**	2.376***	2.023**	2.964***
	(4.111)	(4.814)	(4.905)	(4.476)	(5.122)	(4.892)
Night	-0.529	-0.873	0.946	-0.505***	-0.777	-0.960
	(0.863)	(1.560)	(1.785)	(0.820)	(1.442)	(1.292)
Observations	6,064	6,064	6,064	6,064	6,064	6,064

Standard errors in parentheses- Bootstraps 100 reps; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows results of quantile fixed effects regressions of fine difference on variables (shown in table) and controlling for days in the week that drivers were pulled over for no inspection sticker. Column 1 is results from police officer fixed effects regression. Columns 2 to 6 are results from quantile FE regression with quantile 0.1, 0.25, 0.5, 0.75, and 0.9 respectively.

Table 2.13 Summary statistics of variables used in analysis of police officer sequential decisions

	Daily sequences		Hourly sequences	
	(1)	(2)	(3)	(4)
Fine difference	-39.80	-40.36	-38.05	-38.52
	(51.00)	(52.66)	(50.19)	(52.38)
In-town driver	0.273	0.245	0.276	0.237
	(0.446)	(0.430)	(0.447)	(0.425)
In-state driver	0.866	0.857	0.863	0.850
	(0.341)	(0.350)	(0.344)	(0.357)
Black driver	0.0777	0.0469	0.0876	0.0463
	(0.268)	(0.211)	(0.283)	(0.210)
Hispanic driver	0.0526	0.0436	0.0502	0.0371
	(0.223)	(0.204)	(0.218)	(0.189)
Asian driver	0.0290	0.0254	0.0306	0.0254
	(0.168)	(0.157)	(0.172)	(0.157)
Female driver	0.380	0.384	0.390	0.396
	(0.485)	(0.486)	(0.488)	(0.489)
Age 16-21	0.146	0.160	0.126	0.142
	(0.353)	(0.366)	(0.332)	(0.349)
Age 22-30	0.257	0.252	0.254	0.247
	(0.437)	(0.434)	(0.436)	(0.431)
Age >50	0.157	0.154	0.168	0.165
	(0.364)	(0.361)	(0.374)	(0.371)
Commercial DL	0.0299	0.0300	0.0291	0.0291
	(0.170)	(0.171)	(0.168)	(0.168)
Night	0.323	0.340	0.261	0.275
	(0.468)	(0.474)	(0.439)	(0.447)
State police	0.242	0.256	0.264	0.291
	(0.428)	(0.436)	(0.441)	(0.454)
PO strictness (day)	0.483	0.490		
	(0.371)	(0.371)		
Prev driver ticketed (day)	0.486	0.492		
	(0.500)	(0.500)		
Override fail		0.0151		0.0138
		(0.122)		(0.117)
Distance to court		67.04		69.53
		(290.4)		(292.9)
Property value pc		87,244.3		85,935.8
		(51,093.6)		(46,752.3)
PO strictness (hour)			0.489	0.501
			(0.418)	(0.425)
Prev driver ticketed (hour)			0.497	0.508
			(0.500)	(0.500)
Including Boston	Y	N	Y	N
Observations	67,409	56,374	33,783	26,156

Note: Mean of each variable with standard deviation in parentheses.

Table 2.14 The effect of driver characteristics on police officer daily sequential discretionary decisions

(a) Driver characteristics

	Receiving a ticket		Fine difference	
In-town driver	-0.032***	-0.040***	-2.393***	-3.146***
	(0.003)	(0.006)	(0.351)	(0.623)
In-state driver	-0.025***	-0.026***	-5.515***	-5.862***
	(0.004)	(0.005)	(0.445)	(0.600)
Black driver	0.002	-0.003	-1.028	-1.842*
	(0.006)	(0.009)	(0.701)	(1.041)
Hispanic driver	0.059***	0.059***	5.817***	5.376***
	(0.006)	(0.009)	(0.674)	(0.896)
Asian driver	0.051***	0.051***	4.433***	4.751***
	(0.007)	(0.008)	(0.865)	(0.962)
Female driver	-0.051***	-0.049***	-4.621***	-4.902***
	(0.003)	(0.004)	(0.299)	(0.415)
Age 16-21	0.056***	0.059***	2.289***	2.571***
	(0.004)	(0.005)	(0.439)	(0.637)
Age 22-30	0.040***	0.041***	2.669***	2.910***
	(0.003)	(0.004)	(0.357)	(0.454)
Age >50	-0.046***	-0.040***	-2.374***	-2.162***
	(0.004)	(0.004)	(0.419)	(0.462)
Commercial DL	-0.059***	-0.057***	-5.513***	-5.721***
	(0.007)	(0.008)	(0.836)	(1.038)
Black * Night	0.005	0.010	1.313	3.292*
	(0.010)	(0.012)	(1.159)	(1.772)
Including Boston	Y	N	Y	N
Observations	80,742	67,820	80,742	67,820

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows results of regressing dummy variable whether driver was ticketed (column 1 and 2) and fine difference (column 3 and 4) on variables (shown in table 2.14a and 2.14b) and controlling for days in the week that drivers were pulled over with police officer fixed-effects model and clustering over municipalities.

(b) Other characteristics

	Being ticketed		Fine difference	
Previous driver ticketed	-0.157***	-0.177***	-11.240***	-12.758***
	(0.004)	(0.009)	(0.417)	(0.721)
Night	-0.013***	-0.015***	-1.711***	-1.992***
	(0.003)	(0.005)	(0.374)	(0.612)
State police	0.091***	0.126***	14.878***	17.641***
	(0.014)	(0.023)	(1.655)	(3.843)
PO strictness (day)	1.119***	1.129***	81.342***	84.230***
	(0.007)	(0.013)	(0.775)	(1.508)
Override fail		0.077***		2.004
		(0.029)		(4.581)
Distance to court		<-0.0001		<-0.0001
		(<0.0001)		(0.001)
Property value pc		<-0.0001**		<-0.0001
		(<0.0001)		(<0.0001)
Including Boston	Y	N	Y	N
Observations	80,742	67,820	80,742	67,820

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows results of regressing dummy variable whether driver was ticketed (column 1 and 2) and fine difference (column 3 and 4) on variables (shown in table 2.14a and 2.14b) and controlling for days in the week that drivers were pulled over with police officer fixed-effects model and clustering over municipalities.

Table 2.15 The effect of driver characteristics on police officer hourly sequential discretionary decisions

(a) Driver characteristics

	Being ticketed		Fine difference	
In-town driver	-0.010***	-0.012***	-1.002**	-1.665**
	(0.003)	(0.004)	(0.441)	(0.729)
In-state driver	-0.013***	-0.009**	-4.963***	-5.248***
	(0.004)	(0.004)	(0.553)	(0.681)
Black driver	-0.008	-0.007	-1.231	-2.128
	(0.006)	(0.008)	(0.792)	(1.397)
Hispanic driver	0.032***	0.023***	4.762***	3.782***
	(0.006)	(0.008)	(0.856)	(1.392)
Asian driver	0.034***	0.022***	1.621	0.638
	(0.008)	(0.008)	(1.053)	(1.569)
Female driver	-0.029***	-0.024***	-2.873***	-2.816***
	(0.003)	(0.003)	(0.372)	(0.516)
Age 16-21	0.026***	0.024***	-0.029	-0.352
	(0.004)	(0.004)	(0.575)	(0.840)
Age 22-30	0.018***	0.017***	1.031**	1.030**
	(0.003)	(0.003)	(0.445)	(0.513)
Age >50	-0.034***	-0.025***	-1.287**	-0.633
	(0.004)	(0.005)	(0.512)	(0.648)
Commercial DL	-0.041***	-0.032***	-3.314***	-2.736**
	(0.008)	(0.008)	(1.054)	(1.334)
Black * Night	0.016	0.019*	-0.296	2.060
	(0.010)	(0.011)	(1.431)	(2.177)
Including Boston	Y	N	Y	N
Observations	40,439	31,426	40,439	31,426

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows results of regressing dummy variable whether driver was ticketed (column 1 and 2) and fine difference (column 3 and 4) on variables (shown in table 2.15a and 2.15b) and controlling for days in the week that drivers were pulled over with police officer fixed-effects models and clustering over municipalities.

(b) Other characteristics

	Being ticketed		Fine difference	
Previous driver ticketed	-0.467***	-0.545***	-33.446***	-40.300***
	(0.005)	(0.014)	(0.644)	(1.516)
Night	-0.004	-0.003	-0.991*	-1.003
	(0.004)	(0.003)	(0.515)	(0.770)
State police	0.021	0.043***	12.050***	14.049***
	(0.016)	(0.011)	(2.277)	(4.334)
PO strictness (hour)	1.454***	1.532***	103.876***	113.491***
	(0.007)	(0.015)	(0.927)	(2.481)
Override fail		-0.003		-5.202*
		(0.009)		(2.922)
Distance to court		<-0.0001		<0.0001
		(<0.0001)		(0.001)
Property value pc		<-0.0001		<0.0001
		(<0.0001)		(<0.0001)
Including Boston	Y	N	Y	N
Observations	40,439	31,426	40,439	31,426

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows results of regressing dummy variable whether driver was ticketed (column 1 and 2) and fine difference (column 3 and 4) on variables (shown in table 2.15a and 2.15b) and controlling for days in the week that drivers were pulled over with police officer fixed-effects models and clustering over municipalities.

Table 2.16 The effect of driver characteristics on police officer discretionary decisions on issuing fines at the end of month for the full sample, samples of drivers receiving tickets or warnings only

(a) Driver characteristics

	All violations		Receiving warning		Receiving ticket	
In-town driver	-3.692***	-4.465***	0.670**	0.567	-1.385***	-1.671***
	(0.334)	(0.653)	(0.272)	(0.484)	(0.468)	(0.590)
In-state driver	-8.037***	-8.640***	0.215	0.715	-6.838***	-7.064***
	(0.424)	(0.625)	(0.429)	(0.718)	(0.461)	(0.518)
Black driver	-1.505**	-2.643***	-0.969	-1.206	-2.552***	-3.458***
	(0.703)	(0.972)	(0.623)	(1.077)	(0.861)	(1.255)
Hispanic driver	7.217***	7.038***	2.238***	0.697	1.215*	1.846**
	(0.644)	(0.894)	(0.625)	(1.327)	(0.727)	(0.810)
Asian driver	6.639***	7.025***	1.762**	2.264***	0.909	1.371
	(0.823)	(0.980)	(0.770)	(0.854)	(0.950)	(1.188)
Female driver	-5.739***	-6.109***	-0.264	-0.429	-0.823**	-1.015**
	(0.284)	(0.394)	(0.245)	(0.305)	(0.363)	(0.449)
Age 16-21	4.899***	5.299***	-1.855***	-1.797***	-1.443***	-1.428**
	(0.413)	(0.575)	(0.381)	(0.461)	(0.489)	(0.651)
Age 22-30	3.625***	3.925***	0.344	0.527	-0.673*	-0.630
	(0.338)	(0.419)	(0.305)	(0.355)	(0.407)	(0.445)
Age >50	-2.882***	-2.623***	0.921***	0.907**	1.524***	1.655***
	(0.402)	(0.468)	(0.329)	(0.396)	(0.551)	(0.512)
Commercial DL	-7.531***	-7.691***	-0.334	-0.738	-3.658***	-3.502**
	(0.791)	(0.946)	(0.648)	(0.809)	(1.083)	(1.397)
Black * Night	1.304	1.562	-0.366	0.491	-0.413	0.010
	(1.107)	(1.575)	(0.997)	(1.603)	(1.336)	(2.122)
Including Boston	Y	N	Y	N	Y	N
Observations	112,674	99,201	62,588	54,398	50,086	44,803

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows results of regressing fine difference on variables (shown in table 2.16a and 2.16b) and controlling for days in the week that drivers were pulled over with police officer fixed effects and clustering over municipalities.

(b) Other characteristics

	All violations		Receiving warning		Receiving ticket	
End of month	0.990***	1.146**	0.217	0.238	0.457	0.663
	(0.318)	(0.460)	(0.283)	(0.391)	(0.389)	(0.447)
State police	31.176***	35.946***	7.299***	9.631***	2.936	3.340
	(1.369)	(3.845)	(1.325)	(3.612)	(2.224)	(2.661)
Night	-1.902***	-2.140***	-0.920***	-0.948**	-0.842*	-0.840
	(0.342)	(0.613)	(0.300)	(0.473)	(0.430)	(0.602)
Override fail		5.329		-12.650**		3.161*
		(5.859)		(5.611)		(1.722)
Distance to court		-0.001		0.001		0.0003
		(0.001)		(0.001)		(0.001)
Property value pc		-0.00004**		-0.000004		0.00001
		(0.00002)		(0.00001)		(0.000009)
Including Boston	Y	N	Y	N	Y	N
Observations	112,674	99,201	62,588	54,398	50,086	44,803

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows results of regressing fine difference on variables (shown in table 2.16a and 2.16b) and controlling for days in the week that drivers were pulled over with police officer fixed effects and clustering over municipalities.

Table 2.17 The effect of driver characteristics on police officer discretionary decisions on issuing fines at the end of month for samples of drivers who speed, fail to stop, or have no inspection sticker.

(a) Driver characteristics

	Speeding violation		Failure to stop		No inspection sticker	
In-town driver	-4.711***	-5.426***	-0.807**	-1.050*	-1.749**	-1.835**
	(0.429)	(0.829)	(0.322)	(0.607)	(0.706)	(0.831)
In-state driver	-8.921***	-9.060***	-2.315***	-3.575***	-0.057	0.696
	(0.502)	(0.654)	(0.506)	(1.072)	(1.348)	(1.841)
Black driver	-1.881**	-2.806**	0.214	-0.430	-2.868*	-2.649
	(0.925)	(1.099)	(0.630)	(1.096)	(1.472)	(2.221)
Hispanic driver	8.172***	8.432***	3.645***	4.811***	-1.294	-1.445
	(0.883)	(1.193)	(0.565)	(0.844)	(1.179)	(1.415)
Asian driver	7.861***	8.095***	2.085***	1.641*	-1.132	-0.702
	(1.097)	(1.355)	(0.686)	(0.849)	(2.107)	(3.275)
Female driver	-6.785***	-6.892***	-3.009***	-3.092***	-3.026***	-3.001***
	(0.349)	(0.435)	(0.296)	(0.454)	(0.665)	(0.799)
Age 16-21	8.048***	8.228***	2.664***	3.305***	1.230	1.039
	(0.494)	(0.652)	(0.496)	(0.769)	(1.021)	(1.143)
Age 22-30	4.400***	4.433***	1.325***	1.486**	1.250*	1.510*
	(0.420)	(0.512)	(0.351)	(0.577)	(0.703)	(0.913)
Age >50	-3.327***	-3.054***	-3.223***	-2.970***	-4.856***	-4.303***
	(0.504)	(0.598)	(0.390)	(0.607)	(0.974)	(1.153)
Commercial DL	-9.333***	-9.264***	-3.537***	-2.948***	-1.359	-0.591
	(0.995)	(1.024)	(0.851)	(0.988)	(1.628)	(1.919)
Black * Night	1.518	1.668	-0.688	1.572	4.655	2.606
	(1.442)	(1.844)	(1.002)	(2.035)	(3.027)	(5.214)
Including Boston	Y	N	Y	N	Y	N
Observations	78,410	72,149	21,532	15,410	6,064	5,467

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows results of regressing fine difference on variables (shown in table 2.17a and 2.17b) and controlling for days in the week that drivers were pulled over with police officer fixed effects and clustering over municipalities.

(b) Other characteristics

	Speeding violation		Failure to stop		No inspection sticker	
End of month	1.212***	1.107**	0.497	0.938*	0.200	0.378
	(0.395)	(0.562)	(0.338)	(0.525)	(0.725)	(1.046)
State police	29.735***	30.206***	2.656	14.710***	2.348	3.941
	(2.023)	(4.606)	(1.846)	(4.072)	(4.112)	(5.648)
Night	-2.130***	-2.210***	-0.198	-0.339	-0.531	-0.509
	(0.427)	(0.723)	(0.373)	(0.509)	(0.864)	(0.956)
Mph over limit	-1.672***	-1.657***				
	(0.055)	(0.184)				
Mphol * z15-29	-1.467***	-1.441***				
	(0.058)	(0.161)				
Mphol * z30-44	-0.796***	-0.781***				
	(0.048)	(0.137)				
Mphol * z55-65	0.727***	0.783***				
	(0.054)	(0.175)				
Override fail		5.094		8.998***		0.985
		(5.489)		(3.423)		(5.689)
Distance to court		-0.0002		-0.001		0.001
		(0.001)		(0.001)		(0.002)
Property value pc		-0.00004*		-0.00004***		-0.00002*
		(0.00002)		(0.00002)		(0.000008)
Including Boston	Y	N	Y	N	Y	N
Observations	78,410	72,149	21,532	15,410	6,064	5,467

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows results of regressing fine difference on variables (shown in table 2.17a and 2.17b) and controlling for days in the week that drivers were pulled over with police officer fixed effects and clustering over municipalities.

Table 2.18 The effect of driver characteristics on police officer discretionary decisions on issuing tickets at the end of month.

(a) Driver characteristics

	Full sample	Speeding	Failure to stop	No inspection sticker
In-town driver	-0.057***	-0.060***	-0.022*	-0.035**
	(0.006)	(0.007)	(0.013)	(0.017)
In-state driver	-0.060***	-0.057***	-0.069***	0.016
	(0.005)	(0.006)	(0.021)	(0.036)
Black driver	-0.003	-0.012	-0.013	-0.042
	(0.008)	(0.008)	(0.022)	(0.044)
Hispanic driver	0.079***	0.060***	0.098***	-0.024
	(0.009)	(0.011)	(0.017)	(0.029)
Asian driver	0.066***	0.059***	0.034**	-0.015
	(0.010)	(0.011)	(0.017)	(0.066)
Female driver	-0.070***	-0.055***	-0.063***	-0.059***
	(0.004)	(0.004)	(0.009)	(0.016)
Age 16-21	0.090***	0.072***	0.067***	0.027
	(0.005)	(0.005)	(0.016)	(0.023)
Age 22-30	0.053***	0.042***	0.032***	0.033*
	(0.004)	(0.004)	(0.011)	(0.018)
Age >50	-0.052***	-0.038***	-0.060***	-0.083***
	(0.005)	(0.005)	(0.012)	(0.023)
Commercial DL	-0.078***	-0.083***	-0.058***	-0.010
	(0.009)	(0.009)	(0.020)	(0.039)
Black * Night	0.019	0.004	0.032	0.042
	(0.012)	(0.012)	(0.041)	(0.105)
Including Boston	N	N	N	N
Observations	99,201	72,149	15,410	5,467

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows results of regressing dummy variable whether driver was ticketed on variables (shown in table 2.18a and 2.18b) and controlling for days in the week with police officer fixed effects models and clustering over municipalities where drivers were pulled over. Columns 1 display results of full sample; column 2, 3, 4 include drivers with speed violation, failure to stop, and no inspection stickers.

(b) Other characteristics

	Full sample	Speeding	Failure to stop	No inspection sticker
End of month	0.009**	0.008*	0.018*	0.011
	(0.004)	(0.005)	(0.010)	(0.020)
State police	0.385***	0.392***	0.289***	0.076
	(0.038)	(0.044)	(0.082)	(0.116)
Night	-0.015***	-0.022***	-0.006	-0.009
	(0.006)	(0.006)	(0.011)	(0.019)
Mph over limit		0.029***		
		(0.002)		
Mphol * z15-29		-0.006***		
		(0.001)		
Mphol * z30-44		-0.002***		
		(0.001)		
Mphol * z55-65		0.000		
		(0.002)		
Override fail	0.110**	0.075	0.180***	0.027
	(0.049)	(0.047)	(0.068)	(0.113)
Distance to court	-0.000**	-0.000*	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Property value pc	-0.000***	-0.000***	-0.000***	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Including Boston	N	N	N	N
Observations	99,201	72,149	15,410	5,467

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows results of regressing dummy variable whether driver was ticketed on variables (shown in table 2.18a and 2.18b) and controlling for days in the week with police officer fixed effects models and clustering over municipalities where drivers were pulled over. Columns 1 display results of full sample; column 2, 3, 4 include drivers with speed violation, failure to stop, and no inspection stickers.

CHAPTER 3
The effect of police officer characteristics on their discretionary decisions

3.1 Background

While research shows that driver characteristics influence police officer discretionary decisions (Donohue and Levitt (2001), Antonovics and Knight (2009), Anwar and Fang (2006), and Anbarci and Lee (2014)), a few research examines the effect of police officer characteristics. The main reason is that data on police officer characteristics available for research is limited.

Police officer decisions can vary for the same context. For example, Tyler Perry, a filmmaker and TV show producer accused Atlanta police officers of pulling him over because he is black.[1] In February 24th 2012, on Perry's way to go to Hartsfield-Jackson Atlanta International Airport, two white police officers pulled him over for making a left turn from a right lane. Perry explained that he made the turn in order to ensure that he was not being followed. However, the two police officers kept questioning him and refused to let him go; to Perry, their behavior was so hostile. The third police officer, who was black, arrived not long after and immediately recognized Perry. The police officers let Perry go without any penalty or warning. The report said that the police officers were working on an auto theft task force and thought Perry's car was similar to one of the stolen cars. From radio traffic broadcast that night, one of the white police officers was recorded as follows: "I really did not know who that dude was." Interactions like these raises public concerns about if and how police officer characteristics influence discretionary decisions.

[1] "Atlanta police clear white officers of profiling in Tyler Perry case" by CNN Wire Staff, September 12th, 2012

In this chapter, we examine the effects of police officer characteristics on discretionary decisions and whether the discretion varies across these characteristics, including race, gender and work experience. We use data on traffic citations recorded by Boston police officers in April and May 2001. We find that female, black, Asian, and experienced police officers give higher fine difference than male, white, or less-experienced police officers. Examining if police officers are more lenient toward drivers of their same race, we show that white drivers receive the most favor regardless of police officer race. Black and Hispanic officers give more favor to drivers of their same race than to Hispanic and black drivers, respectively.

This study contributes to the literature on police officer discretion in several ways. First, police officer discretion is defined by the difference between real fine and the fine suggested in the regulation for the same violation. Second, we control for extensive factors that might influence police officer decisions such as characteristics of drivers and police officers, violation severity, and the day of the week that drivers were pulled over. Third, the study is the first to show quantitatively the influence of police officer characteristics on discretionary decisions. Forth, we are able to identify differences in police officer discretion across the race and the gender of the police officer and the driver. Particularly, we investigate the difference between decisions of police officers to drivers of the same race and drivers of other races and if the pattern varies across police officer race.

3.2 Literature review

To our knowledge, there is limited research on the effect of police officer characteristics on the decision-making process of police officers. One potential reason is that data on police officer characteristics is not publicly available. While several studies have investigated the effect of police officer race and conclude that police officer decisions on arresting, stopping, and searching vary across police officer race, less is known on the impacts of other characteristics of police officers such as work experience and gender.

Donohue and Levitt (2001) investigate the effect of police officer race on policing and decisions of arrests. The data is a 6-year panel data of 122 U.S. cities with the rate of crime arrests, the proportion of white/nonwhite police officers, and other characteristics of the cities. They use city and time fixed-effects models and the size and racial composition of fire departments as an instrument. They conclude that an increase in the number of police officers of a given race is associated with an increase in the number of arrests of suspects of other races but have little impact on the number of arrests of same race suspects. However, this study only considers the proportion of nonwhite/white police officers. In other words, the data in their study is at city level while our study examines the decisions of police officer on each specific traffic violation case.

Anwar and Fang (2006) assume that police officers, before making any decisions on vehicle searches, observe several characteristics of drivers that are correlated with the likelihood that drivers carry drugs. However those characteristics are unknown to drivers. The authors use traffic stop data from the Florida Highway Patrol between January 2000 and November 2001, controlling for not only race but also other characteristics of drivers and police officers that may influence police officer decisions such as age, in-state status, the time when drivers were pulled over, and the rank of police officers. Their insight is that if there is no racial bias, the search rates and success rates of finding contraband should be independent of driver race and in the same rank order according police officer race. They fail to reject the hypothesis that there is no racial discrimination. But they show that search rates and success rates vary across police officer race.

Alternatively, Antonovics and Knight (2009) assume that driver characteristics which influence police officer decisions are known to both drivers and police officers. The authors argue that if police officers have no racial preference, the search rates across driver races will be independent of police officer race, given that police officers have the same search costs for drivers of different race. From data on traffic stops in Boston for the two-year period starting in April 2001, they find that police officers are more likely to search vehicles of drivers whose race is different from theirs. However, the assumption that the cost difference of searching white and black drivers are the same to white and black officers may not be hold. In addition, the dependent variable is whether police officer conduct a search. Therefore, we only know the difference in probability of being searched among drivers of the same race with other groups.

Anbarci and Lee (2014) investigate police officer decisions but focus on one different aspect: police officer discretion on giving speeding discount. Speed discounting happens when the reported speed is lower than the actual speed. According to Massachusetts laws, drivers who speed 10 miles per hour or less over the speed limit will be ticketed with a flat rate of $50. After that, fines rise by $10 for each additional mile over the limit. The authors argue that a police officer will favor a group of drivers if the police officer is more likely to write down the speeding ticket of 10 miles per hour over the speed limit instead of the actual speed (from 11 to 14 miles per hour over the speed limit) for that group. The data includes Boston traffic violations between April 2001 and November 2002 with 14,253 speeding tickets and 1,984 warnings. Using the same model as in Anwar and Fang (2006), they find no racial discrimination. Using probit model to estimate the probability of being ticketed at 10, conditional on actual speed between 10 and 14 miles per hour over speed limit. Difference-in-difference model is used with the dependent variable is the dummy variable of whether a driver receives a ticket at 10 or not, conditional on the driver receives ticket and the reported speed between 10 and 14 miles per hour, controlling for other driver characteristics such as gender, age, and resident status and police officer characteristics such as gender, age, work experience.

Their study shows that African-American police officers are stricter than their Hispanic and white counterparts. Hispanic police officers are stricter with Hispanic drivers than with white drivers. African-American police officers are less lenient with white drivers than white police officers are. Moreover, minority police officers are stricter with minority drivers than with white drivers. Male or young police officers are more likely to give speed discounting. In this research, the authors only have data on the reported speed written in citation, not the real speed. They, therefore, assume that all drivers who actually speed at 10 miles per hour over the speed limit will only receive oral warnings instead of citations. And drivers whose speed was written at 10 over the limit were the ones receiving speed discounting from police officers. However, it may not be true for all cases. Using the same data, we can see that police officers even issue ticket to drivers who speed 1 mile per hour over speed limit. Therefore, there will be many citations in which drivers were not received any speed discounting and cited at 10 miles per hour over the speed limit.

Sanga (2014) examines traffic stops made by officers in the Oakland Police Department, California from 2005 to 2010. Using OLS regression and controlling for day of week, year, and interaction of location and time to look at the relationship of officer race and number of stops, he finds that officer race has a small effect on levels of leniency. He suggests that this does not indicate discrimination. In contrast, controlling for day of week, year, officer shift assignment and using officer fixed effects, he finds that the same officers favor drivers of their own race in some neighborhoods but do not favor drivers of their own race in other neighborhoods. He concludes that where one is stopped may be more important than by whom one is stopped.

3.3 Boston traffic violation data

The first set of data comes from the Massachusetts Registry of Motor Vehicles. In July 2000, the Massachusetts legislature passed Chapter 228 of the Acts of 2000, "An Act Providing for the Collection of Data Relative to Traffic Stops", which requests to collect information of traffic violations to "identify and eliminate any instances of unlawful racial and gender profiling by police." Accordingly, police officers were requested to record race, gender, address and other characteristics of drivers who receive a citation for traffic violation. Police officers also recorded the police agency, the reason, time, and location where a driver was stopped as well as characteristics of the vehicle. For speeding violations, speed over the speed limit and speed zone at which a driver was pulled over were recorded. We are able to get the data for traffic violations in April and May 2001.

The second set of data comes from the Boston Police Department. This is unique data on Boston police officers including police officer ID, full name, rank, badge, organization, race, gender and year appointed. We then merge both data sets in order to collate data on traffic citations recorded by Boston police officers in April and May 2001 by using police officer ID. In total, we are able to match 12,504 observations. After dropping missing information on either driver or police officer characteristics, we have a final sample of 8,598 observations, including 3,161 tickets and 5,437 warnings. For each observation, the data includes driver characteristics including race, gender, age, in-town status, in-state status, if he/she owns a commercial driver license as well as police officer characteristics including race, gender, and work experience, fine amount, and types of traffic violation.

3.4 Econometric model of police officer discretionary behavior

To examine the determinants of police officer discretionary behavior, we deploy the regression model:

$$Dif_{dp} = \beta_0 + \beta_1 Driver_{dp} + \beta_2 Police_{dp} + \varepsilon_{dp} \tag{3.1}$$

Dependent variable (Dif_{dpm}) is the difference between the actual fine amount and the suggested fine amount which was issued to driver d in municipality m by police officer p for a traffic violation.

$Police_p$ includes dummy variables of whether a police officer is female, black, Hispanic, and Asian. We create two dummy variables indicating whether a police officer work experience is less than 5 years and from 10 to 15 years (from 5-10 years as a reference group).

$Driver_d$ includes dummy variables of whether a driver is black, Asian, or Hispanic (white drivers as the reference group), female, in-town, and in-state driver. It also includes dummy variables indicating driver's age group: 16-21, 22-30, or greater than 51 (drivers aged 31-50 are the reference group), and whether a driver has a commercial drivers license. We control for several variables regarding the violation such as whether a driver was stopped at night, and the day of a week. In the data, the time when a driver was stopped is rounded backward. For example, if a police officer pulled over a driver any time from 4:00 PM to 4:59 PM, the time reported in the traffic citation would be 4:00 PM. A dummy variable, night, which is equal to 1 if a driver was stopped from 6PM to 5AM and 0 otherwise and an interaction term of whether a driver is black and being pulled over at night are created.

For speeding violation in Boston, speed limits range from 20 to 40 miles per hour. We create two dummy variables whether a driver was pulled over in zone of less than

30 miles per hour and over 30 miles per hours. We create an interaction term of speed over the limit with speed zone where driver was pulled over to see whether speeding in different zones will be treated differently.

We then examine whether police officers treat drivers of the same race equally to drivers of a different race and how the differences in treatment vary across races and gender. We include all interactions of police officer race with driver race, the group of white police officers writing a citation to white drivers as a control group. We estimate using the following model:

$$Dif_{dp} = \beta_0 + \beta_1 Driver_{dp} + \beta_2 Pol_{dp} + \beta_3 Interactions_{dp} + \varepsilon_{dp} \tag{3.2}$$

Since our sample includes officers and drivers whose race is either black, white, Hispanic, or Asian, when interacting and leaving out citations in which white police officers wrote citations to white drivers as control group, we have 15 interaction terms in total. We also create an interaction term indicating cases in which female police officer wrote a citation to female driver to see whether there are different treatments across gender.

3.5 An analysis of Boston police officer discretionary decisions

Table 3.1 shows the number of tickets and warnings written across both police officer race and driver race. Of the 8,598 citations, 5,001 citations (58.2%) are written to white drivers, 2,222 citations (25.8%) to black drivers, 912 citations (10.6%) to Hispanic drivers, and 463 citations (5.4%) to Asian drivers. Compared with police officers of other races, white police officers issue the highest number of citations to drivers of each race group. White police officers issue 3,128 citations to white drivers, representing 57.9% citations issued by white police officers. And white police officers issue an average $41.44 lower than the suggested fine amount to white drivers.

Asian police officers are stricter in issuing fines compared to police officers of other races since they issue lowest discretion in fine difference. Black police officers are strictest with Hispanic drivers while Hispanic and Asian police officers are strictest with black drivers. White police officers are most lenient with black drivers.

Summary statistics of variables used in investigating Boston police officer discretionary decisions are presented in Table 3.2. Six columns present six different samples: full sample, drivers who receive warnings, receive tickets and separate traffic violations including speeding violation, failure to stop and no inspection sticker. With the full sample, on average, a driver in Boston receives a $39.4 reduction in the fine amount for their traffic violation. And a driver who is pulled over for a speeding violation receives more favor than a driver who is pulled over for failure to stop or no inspection sticker, a $50.46 reduction compared to $32.37 and $17.98, respectively. Of the drivers who are pulled over by Boston police officers, 44.2% are in-town drivers, 91.2% are in-state drivers, 35.4% are female drivers, and only 2.71% own a commercial driver license. Among all drivers who are pulled over, 17.9% are older drivers, 7.65% are young drivers from 16 to 21 years old, 28.7% are young drivers from 22 to 30 years old, and 45.75% are middle-aged drivers from 31 to 50 years old. 1,857 drivers (21.6%) were pulled over at night.

For speeding violation, drivers are pulled over at 12.87 miles per hour above the speed limit. Of 3,042 citations for speeding violations, 516 citations (14.8%) are written at a zone lower than 30 miles per hour and 2,552 citations (73.2%) are written at a zone of 30 miles per hour.

Police officers who have work experience from 10 to 15 years write 2,898 citations (33.7%) and police officers who have less than 5 years write 860 citations (10%). Only 500 citations (5.8%) are written by female police officers. Among police officers who write citations in April and May of 2001, 2,049 (23.8%) citations are written by black police officers, 1,020 (11.9%) by Hispanic police officers, 124 (1.44%) by Asian police officers, and 5.405 (49.9%) by white police officers.

Tables 3.3 present estimates of model specified in Equation 3.1 for the full sample in columns 1 and 2, the sample of drivers receiving only warnings in columns 3 and 4, and the sample of drivers receiving only tickets in columns 5 and 6. When considering the full sample, in-town drivers receive an average of $2.22 lower in fine difference than out-of-town drivers, compared to $2.92 when police officer characteristics are omitted. The corresponding numbers for in-state drivers and out-of-state drivers are $4.41 and $4.95. When controlling for police officer characteristics, the estimates increase, which suggests that police officers characteristics have an effect on their discretionary decisions.

Police officers treat black drivers more leniently ($2.36 lower) and treat Hispanic and Asian drivers stricter ($4.97 and $8.84 higher, respectively) than white drivers with regard to fine difference. Female drivers, drivers who own commercial driver license, and older drivers also receive more favor from police officers, $5.29, $9.09, and $3.89 lower in fine difference compared to male drivers and other drivers, middle-aged drivers from 31 to 50, respectively.

We also find that police officer characteristics such as race and gender influence their discretion. Although female police officers issue fewer citations, for the same violation, female police officers give an average of $14.79 higher in fine difference than their male police officer counterparts. Black, Hispanic, and Asian police officers are stricter than white police officers, giving $2.43, $9.76, and $28.58 higher in fine difference, respectively.

Work experience also influences police officer discretionary decisions. The more work experience police officers have, the stricter their decisions are. Police officers with 10 to 15 years of work experience give an average of $13.88 higher in fine difference than police officers with 5 to 10 years of work experience while police officers with less than 5 years of work experience give \$4.79 lower in fine difference. When examining sample of drivers receiving ticket only, we find that police officers are more lenient toward black and Hispanic drivers than toward white drivers.

When examining a sample of drivers who receive tickets only, the estimates for the effect of in-town and in-state drivers are still negative but not significant and the magnitude is small. This suggests that when a police officer decides to issue a ticket, he will treat the driver equally regardless of resident status. However, we find that police officers treat black and Hispanic drivers more leniently than white drivers.

Table 3.4 presents results when looking at sample of drivers who were pulled over for speeding violations (column 1 and 2) and failure to stop (column 3 and 4). For the sample of drivers violating speeding rules, we still find that in-state, female, commercial driver license owned drivers are treated more leniently than out-of-state, male, and other drivers with \$5.7, \$7.24, and \$19.93 lower in fine difference, respectively. Police officers are stricter toward Asian drivers than toward white drivers. The coefficients indicating black driver and Hispanic drivers are positive but not significant.

Female police officers are much stricter than male police officers. On average, female police officers issue \$29.01 higher in fine difference than male police officers. Hispanic and Asian police officers are stricter than white police officers with \$8.79 and \$75.06 higher in fine difference. Less experienced police officers are more lenient while highly experienced police officers are stricter than police officers with work experience from 5 to 10 years.

For speeding violations, more drivers are pulled over at low speed zones (14.8%) than at high speed zones (12.0%). And drivers are pulled over for speeding violations with an average of 12.87 miles per hour over the speed limit. Drivers who are pulled over in low speed zones are treated more leniently than drivers who are pulled over in higher speed zones. If a driver is pulled over in a speed zone below 30 miles per hour, for one mile over the speed limit, the driver receives \$0.72 lower than the amount he will be fined when being pulled over in speed zone of 30 miles per hour. The corresponding fine for being pulled over in speed zone above 30 miles per hour is \$2.34 higher.

When examining the sample of drivers violating failure to stop rules (columns 3 and 4 of table 3.4), we show that the sign and significance of all estimates are similar to the results when examining the full sample, except for the gender of the police officer and if the driver is black. We find that female police officers issue an average of \$2.55 lower in fine difference than male police officers. We also find that police officers are stricter with black, Hispanic, and Asian drivers than white drivers, giving \$5.04, \$4.4, and \$6.62 higher in fine difference, respectively. Police officers are more lenient with in-town, in-state drivers, female drivers, older drivers, and drivers with a commercial drivers license. Hispanic and Asian police officers are stricter than white police officers, giving \$6.53 and \$11.72 higher in fine differences.

Next, we examine if officer discretionary behavior varies across races by including the interactions between officer and driver race and an interaction term to indicate if both driver and officer are female. Table 3.5 presents summary statistics for covariates used in analysis . In total, we have 15 interaction terms across races of police officers and drivers, besides the interaction indicating white police officers giving fines to white drivers as the control group. A large proportion is written by a white officer to a white driver (36.1%), white officer to black driver (16.3%), black officer to white driver (13.4%), and Hispanic officer to white driver (7.65%). Female officers only write 500 out of 8,598 citations (5.82%) and of the 500 citations, 193 citations are given to female drivers. Officers with less than 5 years experience write 860 citations (10%), officers from 5 to 10 year experience write 2,889 citations (33.6%).

On average, police officers issue \$39.40 lower in fine difference to pulled-over drivers. If looking at samples of drivers with speed violation or failure to stop violation, police officers issue an average of \$50.46 and \$32.37 reduction in fine difference. Of all the citations written, 3,044 citations (35.4%) are issued to female drivers, 658 citations (7.65%) to young drivers aged 16-21, 2,468 citations (28.7%) to drivers aged 22-30, 1,539 citations (17.9%) to drivers older than 50, and only 233 citations (0.027%) to drivers with commercial driver license. For speeding violations, drivers are pulled over and issued citations when they drive on average 12.87 miles per hour over the speed limit. Most of drivers are pulled over for speeding in zone of 30 mile per hour (73.2%) while only 12% in speed zone below 30 and 14.8% in speed zone above 30 mile per hour.

Table 3.6b shows how police officers treat drivers of the same race compared to drivers from different races using the model in Equation 3.2. Columns 1, 2, 3 examine police officer discretionary decisions on issuing tickets and columns 4, 5, 6 examine police officer discretionary decisions on the fine amount. Considering the full sample in columns 1 and 4, in-town and in-state drivers are less likely to be ticketed (8.5 and 16.5 percentage point lower) and to be fined (\$2.03 and \$4.4 lower) than out-of town and out-of-state drivers, respectively. If we only examine the number of citations written to local drivers (91.2% to in-state drivers and 44.2% to in-town drivers), we might conclude that police officers are stricter toward local drivers. However, when looking at fine difference, we can see the opposite: Police officers are more lenient toward local drivers. The reason might be that most people who drive in Boston are local drivers. Therefore, they have a higher possibility of being pulled over by police officers.

Female drivers are, on average, 24.8 percentage points less likely to receive a ticket and receive \$5.29 lower in fine difference than male drivers. Police officers are more lenient with older drivers and drivers with a commercial driver license. For speeding violations, the previous conclusion still holds; drivers are treated stricter if they are pulled over in higher speed zones.

We show that female police officers are on average 29 percentage points more likely to issue a ticket and issue an average of $14.57 higher in fine difference than male police officers. The conclusion that the more work experience police officers have, the stricter their decisions will be still remains consistent. Police officers who have 10 to 15 years of work experience are on average 41.7 percentage points more likely to issue a ticket and issue $13.77 higher in fine difference than police officers who have 5 to 10 years of work experience.

We show that white drivers, compared to other drivers, receive the most favor from white, black, Asian, and Hispanic police officers in both probability of being ticketed and fine difference except that white police officers issue black drivers an average of $3.51 lower in fine difference than what the same officers give to white drivers. White police officers are stricter toward Asian drivers than toward other drivers both in terms of the likelihood of ticketing and fine difference.

Black police officers are strictest with Hispanic drivers while Hispanic police officers are strictest with Black drivers compared to other drivers. Black police officers give Hispanic drivers 58.8 percentage points higher in probability of being ticketed and $11.19 higher in fine difference. Hispanic police officers give black drivers 75.6 percentage points higher in receiving a ticket and $16.02 higher in fine difference. Asian police officers are strictest with Hispanic drivers regarding probability of issuing a ticket but strictest with black drivers regarding fine difference.

3.6 Summary

In summary, we show that police officer characteristics influence their discretionary decisions. Female police officers are stricter than male police officers in both probability of issuing tickets and fine amount. Police officers with more work experience are stricter than less experienced police officers. White police officers are more lenient than police officers of other races.

We also show that driver characteristics also influence police officer discretion. Police officers are more lenient toward in-town drivers, in-state drivers, female drivers, older drivers, and drivers owning a commercial drivers license. Black drivers are treated more leniently and Hispanic and Asian drivers are treated stricter than white drivers. Police officers are stricter with young drivers than with middle-aged drivers. For speeding violations, police officers are stricter when pulling drivers over in high speed zones.

Including interactions between driver race and police officer race allow us to investigate the differences in police officer discretionary decisions across races. Interestingly, white drivers have the highest number of citations in our data. However when including all racial interaction terms and controlling for all characteristics of drivers and police officers, we show that white drivers, compared to other drivers, are treated most leniently by police officers of all races in both probability of being ticketed and fine amount. White police officers are strictest with Asian drivers when examining the full sample or single violation such as speeding or failure to stop. Black and Asian police officers are strictest with Hispanic drivers while Hispanic police officers are strictest with black drivers.

Table 3.1 Number of citations categorized across races of police officer and driver

	Police officer race				
Driver race	Black	Hispanic	White	Asian	Total
Black	569	208	1,401	44	2,222
Percentage	27.8	20.4	25.9	35.5	25.8
Fine difference	-42.20	-28.25	-45.79	-10.91	-42.54
	(46.87)	(37.21)	(43.23)	(28.37)	(43.94)
Hispanic	224	97	581	10	912
Percentage	10.9	9.5	10.7	8.1	10.6
Fine difference	-30.07	-34.23	-39.74	-17.5	-36.54
	(34.49)	(37.36)	(37.44)	(28.99)	(36.88)
White	1,155	658	3,128	60	5,001
Percentage	56.4	64.5	57.9	48.4	58.2
Fine difference	-36.79	-36.44	-41.44	-24.42	-39.51
	(40.0)	(39.04)	(37.91)	(30.46)	(38.56)
Asian	101	57	295	10	463
Percentage	4.9	5.6	5.5	8.1	5.4
Fine difference	-42.38	-33.16	-23.86	-15	-28.86
	(44.34)	(36.05)	(33.99)	(24.15)	37.31
Total	2,049	1,020	5,405	124	8,598

This table shows the number of observations in each category of police officer race and driver race. The percentage shows the percentage of citations that are written for that group of drivers over the total citations written by that group of police officers. Fine difference gives the average of fine difference received by drivers in this groups. The standard deviation of the fine difference is in parentheses.

Table 3.2 Summary statistics of variables.

	(1)	(2)	(3)	(4)	(5)
Fine difference	-39.40	-62.12	-0.324	-50.46	-32.37
	(39.90)	(25.72)	(27.89)	(50.49)	(23.94)
In-town driver	0.442	0.455	0.420	0.461	0.439
	(0.497)	(0.498)	(0.494)	(0.499)	(0.496)
In-state driver	0.912	0.923	0.892	0.912	0.914
	(0.284)	(0.267)	(0.310)	(0.284)	(0.280)
Black driver	0.258	0.249	0.275	0.294	0.228
	(0.438)	(0.432)	(0.447)	(0.456)	(0.419)
Hispanic driver	0.106	0.0975	0.121	0.0924	0.111
	(0.308)	(0.297)	(0.326)	(0.290)	(0.315)
Asian driver	0.0538	0.0432	0.0721	0.0381	0.0620
	(0.226)	(0.203)	(0.259)	(0.192)	(0.241)
Female driver	0.354	0.385	0.300	0.397	0.345
	(0.478)	(0.487)	(0.458)	(0.489)	(0.476)
Age 16-21	0.0765	0.0679	0.0914	0.0888	0.0691
	(0.266)	(0.252)	(0.288)	(0.284)	(0.254)
Age 22-30	0.287	0.282	0.297	0.290	0.284
	(0.453)	(0.450)	(0.457)	(0.454)	(0.451)
Age >50	0.179	0.200	0.144	0.165	0.191
	(0.383)	(0.400)	(0.351)	(0.371)	(0.393)
Commercial DL	0.0271	0.0329	0.0171	0.0247	0.0258
	(0.162)	(0.178)	(0.130)	(0.155)	(0.159)
Night	0.216	0.213	0.221	0.177	0.237
	(0.411)	(0.409)	(0.415)	(0.382)	(0.425)
Black PO	0.238	0.225	0.261	0.235	0.230
	(0.426)	(0.418)	(0.439)	(0.424)	(0.421)
Hispanic PO	0.119	0.102	0.148	0.116	0.104
	(0.323)	(0.302)	(0.355)	(0.320)	(0.305)
Asian PO	0.0144	0.00791	0.0256	0.00526	0.0146
	(0.119)	(0.0886)	(0.158)	(0.0723)	(0.120)
Female PO	0.0582	0.0526	0.0677	0.0398	0.0729
	(0.234)	(0.223)	(0.251)	(0.195)	(0.260)
PO exp < 5	0.100	0.126	0.0560	0.0464	0.156
	(0.301)	(0.332)	(0.230)	(0.210)	(0.363)
PO exp 10-15	0.336	0.287	0.419	0.279	0.343
	(0.472)	(0.452)	(0.494)	(0.448)	(0.475)
Mph over limit				12.87	
				(4.110)	
Zone <30				0.148	
				(0.355)	
Zone>30				0.120	
				(0.325)	
Observations	8,598	5,437	3,161	3,042	3,486

Note: Mean of each variable with standard deviation in parentheses.

This table gives summary statistics of variables used in examining Boston police officer discretionary decisions: (1) full sample; (2) receiving warning; (3) receiving ticket; (4) speed violation; (5) failure to stop.

Table 3.3 Boston police officer discretionary decisions

	All violations		Warnings		Tickets	
	(1)	(2)	(3)	(4)	(5)	(6)
In-town driver	-2.917***	-2.217**	0.010	-0.047	-0.023	-0.004
	(0.939)	(0.929)	(0.760)	(0.773)	(1.060)	(1.057)
In-state driver	-4.952***	-4.410***	0.016	-0.333	-1.004	-0.804
	(1.643)	(1.616)	(1.236)	(1.221)	(1.911)	(1.917)
Black driver	-2.656**	-2.359*	-5.785***	-5.633***	-7.176***	-7.033***
	(1.272)	(1.235)	(1.072)	(1.056)	(1.451)	(1.461)
Hispanic driver	3.526**	4.971***	2.743***	3.194***	-7.578***	-7.255***
	(1.372)	(1.370)	(1.006)	(1.020)	(1.709)	(1.740)
Asian driver	9.736***	8.838***	1.367	1.520	-0.291	-0.656
	(1.809)	(1.782)	(1.575)	(1.556)	(1.346)	(1.377)
Female driver	-4.946***	-5.288***	0.281	0.108	1.243	1.088
	(0.894)	(0.873)	(0.695)	(0.688)	(1.096)	(1.090)
Age 16-21	-1.054	-1.012	-2.650*	-2.353	-4.259*	-4.149*
	(1.819)	(1.789)	(1.596)	(1.596)	(2.287)	(2.270)
Age 22-30	-0.635	-0.161	0.224	0.567	-2.007*	-1.969
	(1.031)	(1.010)	(0.812)	(0.801)	(1.201)	(1.220)
Age >50	-3.995***	-3.894***	1.364	1.456	0.002	-0.068
	(1.143)	(1.117)	(0.929)	(0.921)	(1.107)	(1.113)
Commercial DL	-9.163***	-9.086***	-0.335	-0.392	-0.364	-0.804
	(2.600)	(2.573)	(2.322)	(2.339)	(2.793)	(2.808)
Night	1.024	0.314	6.062***	5.314***	-3.057**	-3.002**
	(1.147)	(1.163)	(0.877)	(0.883)	(1.411)	(1.436)
Black * Night	3.358	4.054*	0.387	1.040	-0.794	-0.600
	(2.466)	(2.416)	(2.164)	(2.129)	(3.337)	(3.331)
Black PO		2.432**		-0.244		-3.369**
		(1.075)		(0.917)		(1.382)
Hispanic PO		9.762***		-0.445		-0.633
		(1.354)		(1.104)		(1.287)
Asian PO		28.582***		13.060***		-0.177
		(2.849)		(1.785)		(2.766)
Female PO		14.793***		10.352***		6.740***
		(1.601)		(1.027)		(1.542)
PO exp < 5		-4.786***		2.485**		0.473
		(1.394)		(1.154)		(2.690)
PO exp 10-15		13.878***		5.203***		1.935*
		(0.957)		(0.738)		(1.148)
PO characteristic	N	Y	N	Y	N	Y
Observations	8,598	8,598	5,437	5,437	3,161	3,161

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows results of regressing fine difference on characteristics of drivers and police officers for sample of drivers who received either ticket or warning in columns 1 and 2; Only receiving warning in columns 3 and 4; Only receiving ticket in columns 5 and 6.

Table 3.4 Boston police officer discretionary decisions

	Speed violation		Failure to stop	
In-town driver	-1.869	-1.202	-2.545***	-1.455*
	(1.758)	(1.690)	(0.867)	(0.847)
In-state driver	-5.146*	-5.703**	-4.766***	-3.578**
	(2.924)	(2.906)	(1.530)	(1.497)
Black driver	0.416	0.630	5.234***	5.039***
	(2.108)	(2.048)	(1.215)	(1.203)
Hispanic driver	3.345	4.228	3.632***	4.402***
	(2.864)	(2.811)	(1.366)	(1.289)
Asian driver	7.275*	7.673*	7.411***	6.626***
	(4.331)	(4.131)	(1.750)	(1.704)
Female driver	-7.228***	-7.242***	-3.068***	-3.184***
	(1.589)	(1.538)	(0.847)	(0.815)
Age 16-21	2.955	2.925	1.933	1.181
	(3.151)	(3.031)	(1.713)	(1.647)
Age 22-30	0.332	1.122	0.722	0.489
	(1.903)	(1.845)	(0.986)	(0.959)
Age >50	-2.708	-2.622	-4.018***	-4.383***
	(2.164)	(2.076)	(1.059)	(1.017)
Commercial DL	-19.098***	-19.927***	-7.514***	-7.498***
	(4.796)	(4.521)	(2.157)	(2.087)
Night	0.058	-1.739	-0.579	-0.718
	(2.536)	(2.646)	(1.143)	(1.120)
Black * Night	4.061	4.836	-1.934	-1.316
	(4.520)	(4.459)	(2.175)	(2.137)
Mph over limit	-5.454***	-5.034***		
	(0.413)	(0.449)		
Mphol * z<30	-0.415**	-0.724***		
	(0.202)	(0.206)		
Mphol * z>30	2.905***	2.342***		
	(0.279)	(0.284)		
Black PO		2.828		4.827***
		(2.093)		(0.987)
Hispanic PO		8.785***		6.533***
		(2.507)		(1.381)
Asian PO		75.061***		11.722***
		(10.695)		(3.386)
Female PO		29.013***		-2.548*
		(4.557)		(1.421)
PO exp < 5		-16.638***		-4.401***
		(3.724)		(1.014)
PO exp 10-15		19.677***		11.101***
		(1.965)		(0.934)
PO characteristic	N	Y	N	Y
Observations	3,042	3,042	3,486	3,486

Robust standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01

This table shows results of regressing fine difference on characteristics of drivers and police officers for sample of drivers who were pulled over for speeding violation and failure to stop.

Table 3.5 Summary statistics of variables used in analysis of Boston police officer discretionary decisions with interaction terms.

(a) Driver characteristics

	Full sample	Speed violation	Failure to stop
Fine difference	-39.40	-50.46	-32.37
	(39.90)	(50.49)	(23.94)
In-town driver	0.442	0.461	0.439
	(0.497)	(0.499)	(0.496)
In-state driver	0.912	0.912	0.914
	(0.284)	(0.284)	(0.280)
Female driver	0.354	0.397	0.345
	(0.478)	(0.489)	(0.476)
Age (16-21 years old)	0.0765	0.0888	0.0691
	(0.266)	(0.284)	(0.254)
Age (22-30 years old)	0.287	0.290	0.284
	(0.453)	(0.454)	(0.451)
Age (>50 years old)	0.179	0.165	0.191
	(0.383)	(0.371)	(0.393)
Commercial DL	0.0271	0.0247	0.0258
	(0.162)	(0.155)	(0.159)
Night	0.216	0.177	0.237
	(0.411)	(0.382)	(0.425)
Black * Night	0.0658	0.0667	0.0700
	(0.248)	(0.250)	(0.255)
Mph over limit		12.87	
		(4.110)	
Pulled over at zone<30		0.148	
		(0.355)	
Pulled over at zone>30		0.120	
		(0.325)	
Observations	8,598	3,042	3,486

Note: Mean of each variable with standard deviation in parentheses.

This table gives summary statistics of variables used in examining the cross-race and gender discretion in traffic violation ticketing of Boston police officers.

(b) Police officer characteristics

	Full sample	Speed violation	Failure to stop
Female PO	0.0582	0.0398	0.0729
	(0.234)	(0.195)	(0.260)
Female PO * female driver	0.0224	0.0178	0.0301
	(0.148)	(0.132)	(0.171)
PO experience < 5 y	0.100	0.0464	0.156
	(0.301)	(0.210)	(0.363)
PO experience 10-15 y	0.336	0.279	0.343
	(0.472)	(0.448)	(0.475)
White PO * black driver	0.163	0.208	0.130
	(0.369)	(0.406)	(0.337)
White PO * Hispanic driver	0.0676	0.0661	0.0683
	(0.251)	(0.248)	(0.252)
White PO * Asian driver	0.0343	0.0217	0.0442
	(0.182)	(0.146)	(0.206)
Black PO * white driver	0.134	0.141	0.122
	(0.341)	(0.348)	(0.328)
Black PO * black driver	0.0662	0.0641	0.0686
	(0.249)	(0.245)	(0.253)
Black PO * Hispanic driver	0.0261	0.0174	0.0310
	(0.159)	(0.131)	(0.173)
Black PO * Asian driver	0.0117	0.0122	0.00803
	(0.108)	(0.110)	(0.0893)
Hispanic PO * white driver	0.0765	0.0835	0.0591
	(0.266)	(0.277)	(0.236)
Hispanic PO * black driver	0.0242	0.0194	0.0252
	(0.154)	(0.138)	(0.157)
Hispanic PO * Hispanic driver	0.0113	0.00888	0.0106
	(0.106)	(0.0938)	(0.102)
Hispanic PO * Asian driver	0.00663	0.00427	0.00861
	(0.0812)	(0.0652)	(0.0924)
Asian PO * black driver	0.00512	0.00230	0.00373
	(0.0714)	(0.0479)	(0.0610)
Asian PO * white driver	0.00698	0.00296	0.00832
	(0.0832)	(0.0543)	(0.0908)
Asian PO * Hispanic driver	0.00116	0	0.00143
	(0.0341)		(0.0379)
Asian PO * Asian driver	0.00116	0	0.00115
	(0.0341)		(0.0339)
Observations	8,598	3,042	3,486

Note: Mean of each variable with standard deviation in parentheses.

This table gives summary statistics of variables used in examining the cross-race and gender discretion in traffic violation ticketing of Boston police officers.

Table 3.6 Boston police discretionary decisions with interactions.

(a) Driver characteristics

	Whether driver was ticketed			Fine difference		
	(1)	(2)	(3)	(4)	(5)	(6)
In-town driver	-0.085***	-0.074	-0.095*	-2.030**	-1.184	-1.488*
	(0.032)	(0.057)	(0.050)	(0.929)	(1.690)	(0.848)
In-state driver	-0.165***	-0.196**	-0.193**	-4.397***	-5.796**	-3.536**
	(0.051)	(0.090)	(0.082)	(1.620)	(2.923)	(1.496)
Female driver	-0.248***	-0.205***	-0.187***	-5.279***	-7.250***	-3.198***
	(0.031)	(0.054)	(0.050)	(0.909)	(1.564)	(0.852)
Age 16-21	0.109**	0.084	0.052	-0.938	2.952	1.233
	(0.054)	(0.091)	(0.091)	(1.783)	(3.019)	(1.650)
Age 22-30	0.009	0.013	0.020	-0.125	1.178	0.399
	(0.034)	(0.061)	(0.055)	(1.007)	(1.843)	(0.959)
Age >50	-0.222***	-0.113	-0.270***	-3.946***	-2.711	-4.434***
	(0.041)	(0.076)	(0.064)	(1.120)	(2.078)	(1.019)
Commercial DL	-0.423***	-0.779***	-0.485***	-9.051***	-20.121***	-7.320***
	(0.094)	(0.223)	(0.158)	(2.579)	(4.562)	(2.085)
Night	-0.091**	-0.095	-0.038	0.273	-1.797	-0.976
	(0.043)	(0.089)	(0.065)	(1.168)	(2.674)	(1.128)
Black * Night	0.169**	0.189	-0.089	3.823	3.524	-1.189
	(0.077)	(0.147)	(0.122)	(2.402)	(4.550)	(2.153)
Mph over limit		0.079***			-5.019***	
		(0.008)			(0.452)	
Mphol * z<30		-0.016***			-0.784***	
		(0.005)			(0.206)	
Mphol * z>30		0.046***			2.311***	
		(0.007)			(0.286)	
Observations	8,598	3,033	3,486	8,598	3,042	3,486

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

First three columns are results of probit regression to examine probability of receiving ticket, the last three columns are OLS regression of fine difference on all variables. Column (1) and (4) are for full sample; (2) and (5) speed violation; (3) and (6) failure to stop violation. All regressions control for the day of the week when the driver was pulled over.

(b) Police officer characteristics

	Whether driver was ticketed			Fine difference		
	(1)	(2)	(3)	(4)	(5)	(6)
Female PO	0.290***	1.009***	-0.164	14.571***	29.405***	-2.961
	(0.077)	(0.176)	(0.115)	(2.066)	(5.518)	(1.879)
Fem PO * fem drv	-0.078	-0.038	0.013	0.336	-0.329	0.684
	(0.125)	(0.250)	(0.186)	(3.121)	(8.469)	(2.839)
PO exp < 5 y	-0.381***	-0.777***	-0.292***	-4.662***	-16.900***	-4.211***
	(0.054)	(0.173)	(0.071)	(1.386)	(3.760)	(1.017)
PO exp 10-15 y	0.417***	0.691***	0.606***	13.765***	19.220***	11.099***
	(0.032)	(0.060)	(0.052)	(0.955)	(2.005)	(0.936)
Whi PO * Blk drv	0.118**	0.081	0.255***	-3.506**	-0.607	4.109***
	(0.047)	(0.079)	(0.081)	(1.451)	(2.264)	(1.404)
Whi PO * H drv	0.217***	0.097	0.153	3.716**	3.401	2.429
	(0.060)	(0.109)	(0.093)	(1.703)	(3.362)	(1.490)
Whi PO * As drv	0.520***	0.539***	0.487***	15.470***	17.279***	8.593***
	(0.077)	(0.168)	(0.109)	(2.038)	(5.642)	(1.994)
Blk PO * Whi drv	0.166***	0.079	0.257***	3.464**	2.643	4.073***
	(0.046)	(0.087)	(0.075)	(1.347)	(2.534)	(1.294)
Blk PO * Blk drv	0.384***	0.348***	0.576***	-1.219	6.191	9.426***
	(0.065)	(0.122)	(0.106)	(2.106)	(4.205)	(1.924)
Blk PO * H drv	0.588***	0.456**	0.760***	11.187***	9.979	12.883***
	(0.092)	(0.186)	(0.138)	(2.509)	(6.176)	(2.526)
Blk PO * As drv	0.121	-0.095	0.264	-2.865	-8.108	4.449
	(0.132)	(0.226)	(0.252)	(4.269)	(5.861)	(4.430)
H PO * Whi drv	0.407***	0.478***	0.393***	8.020***	6.897**	6.502***
	(0.057)	(0.101)	(0.100)	(1.689)	(2.952)	(1.780)
H PO * Blk drv	0.756***	0.607***	0.796***	16.019***	17.022***	13.960***
	(0.096)	(0.182)	(0.143)	(2.869)	(6.091)	(2.717)
H PO * H drv	0.693***	0.691**	0.489**	12.219***	10.229	8.080*
	(0.135)	(0.275)	(0.222)	(3.869)	(8.940)	(4.196)
H PO * As drv	0.551***	0.927**	0.418*	9.964**	16.457	7.058
	(0.169)	(0.364)	(0.235)	(4.859)	(11.711)	(4.361)
As PO * Blk drv	1.519***	2.128***	1.309***	35.059***	66.735***	23.872***
	(0.220)	(0.582)	(0.379)	(4.502)	(18.000)	(6.717)
As PO * Whi drv	0.824***		0.304	23.133***	82.691***	4.592
	(0.168)		(0.255)	(4.212)	(11.770)	(4.240)
As PO * H drv	1.609***		1.705***	31.766***		30.080***
	(0.465)		(0.630)	(8.654)		(8.800)
As PO * As drv	1.174**		1.451**	31.666***		25.880**
	(0.458)		(0.729)	(8.708)		(11.521)
Observations	8,598	3,033	3,486	8,598	3,042	3,486

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

First three columns are results of probit regression to examine probability of receiving ticket, the last three columns are OLS regression of fine difference on all variables. Column (1) and (4) are for full sample; (2) and (5) speed violation; (3) and (6) failure to stop violation. All regressions control for the day of the week when the driver was pulled over. (PO: police officer; Whi: white; Blk: black; H: Hispanic; As: Asian; drv: driver)

CHAPTER 4
Police officer discretionary decisions on duration of stops - an analysis from Illinois stop and search data

4.1 Background

The traffic stops and searches are the most common interactions between police officers and citizens. The majority of drivers believe that racial disparity in traffic stops is pervasive, which leads them to distrust of police officers and makes them less likely to cooperate with police officers (Weitzer and Tuch (2002)). As a consequence, the integrity and legitimacy of law enforcement is threatened. Analyzing police officer decisions are, therefore, very important to address public perception that police officers treat drivers unequally.

To stop a vehicle, a police officer must have a reasonable suspicion or legal justification. Driver characteristics such as race, gender, and age cannot serve as valid justification. In addition, any decisions based on such reasons violate the Fourth Amendment of the Constitution which protects against unauthorized searches and seizures. In reality, there are traffic stops that are proved to violate the Fourth Amendment.

On July 18th, 1998, Anne F. Cox was pulled over by Officer Matt McCormick of the Fairfield police officer department for missing a rear registration light.[1] At the time of stop, the police officer called Deputy Dave Zola and asked him to bring his canine to the scene. The police officer, by himself, did not smell cannabis in her vehicle, nor did he have probable reason to request assistance at the scene. Fifteen minutes later, while Officer McCormick was writing the traffic ticket, Deputy Zola arrived.

[1] The People of The State of Illinois, Appellant, v. Anne F. Cox, Appellee. Docket No. 90759-Agenda 5 - January 2002

The canine alerted to the presence of drugs. Later, the police officers found "possible cannabis seeds and residue" on the floorboard and cannabis on her person. Anne was arrested for possession of less than 2.5 grams of a substance containing cannabis. She filed a motion to suppress evidence seized by the law enforcement personnel during the search of her car and her person following a traffic stop. The trial court and the appellate court both affirm that "In this case, the officer lacked reasonable suspicion sufficient to call the canine unit." While the State argued that the dog sniff was justified, the circuit court disagreed and mentioned that "While we will not impose a rigid time limitation on the duration of a traffic stop, we are concerned with the duration of the traffic stop in the present case" and "Officer McCormick should have issued a traffic citation or warning ticket to defendant expeditiously. Had he done so, defendant would had left the scene of the traffic stop prior to the arrival of the canine unit." In addition, the appellate court added that "the Fourth Amendment is violated if the police take 15 minutes to write the traffic ticket." From this case, we notice that the duration of a traffic stop can be a good indicator for police officer decision.

This study examines how driver characteristics and other features of traffic stops affect police officer discretionary decisions including the probability of issuing a ticket, the success rate of finding drugs or contraband, and the duration of stops. To examine police officer discretion, we employ three empirical approaches. First, we assume that if police officers do not take driver characteristics into consideration, the success rate of finding drugs or contraband should be equal across these characteristics. We then apply the Pearson χ^2 test to compare the success rates of finding contraband across groups of drivers. We examine not only the search and success rates in general but also investigate the success rate from three different forms of search: vehicle, driver and passenger, and police dog. Second, we use police officer agency fixed effects in order to examine the effect of driver characteristics on police officer discretionary decisions in the duration of stops. Third, we apply propensity score matching method to investigate police officer discretion in the probability of issuing a ticket, conducting a search, and the duration of stops. We find that police officers consider driver characteristics when making decisions of stopping and searching vehicles.

These findings reveal the following important aspects. First, to our knowledge, this study is the first to examine police officer decisions regarding duration of stops in a statewide study. Several legal reports document the duration of stops. To my knowledge, however, there is no study before this that shows quantitatively the effects of driver characteristics on duration of stops.

Second, this study is also the first to investigate a sample of drivers who are stopped but not searched when examining police officer decisions of stop and search. While most of the research focuses on a group of drivers who are stopped, other looks at group of drivers who are searched and found drugs/contraband, this study, besides these two groups, investigates the group of drivers who are stopped but not searched. According to a report from the U.S. Department of Justice, only 3.5% of all stopped drivers are searched by police officers.[2] So it is important to examine police officer discretionary behavior on making decisions of stopping but not searching as well.

Third, we investigate police officer behavior in duration of stops for sample of drivers who are stopped and searched but for whom no drugs/contraband is found. We do not include drivers who are stopped and found drugs/contraband because the search protocol upon finding drugs can be lengthy. In addition, depending upon the quantity and type of drug, search protocol is not uniform, further obfuscating identification of discretion.

[2]The data used in this report is from the Bureau of Justice Statistics 2011 Police-Public Contact Survey.

4.2 Literature review

There are several methods have been used in the literature to examine police officer discretionary decisions of traffic stop and search. Some use the benchmarking test which compares characteristics of drivers who are stopped and searched with the characteristics of the driving population in the same area (Engel (2008), Walker (2001), Fridell (2004)). Some use the outcome test which compares the success rate of finding drugs/contraband among drivers who are searched (Knowles et al. (2001), Dharmapala and Ross (2004), Anwar and Fang (2006), Antonovics and Knight (2009), Sanga (2009)). However, most of the research focus on the outcome of stops and search such as whether to find contraband or the number of drivers stopped.

Alpert et al. (2006) conduct a field study with observers sitting alongside police officers in Savannah, Georgia. When the police officer notices a suspicious driver/vehicle, observers ask police officers for the reasons that form their suspicions, including: appearance, behavior, time and place, and information. For most of the cases (66%), the reason offered is the behavior of the suspects while only 6% is from the appearance of the driver and/or vehicle. However, the authors conclude that none of the suspect characteristics significantly influence the likelihood of stops, implying that drivers, regardless of race, gender, and socioeconomic status, are equally likely to be stopped after suspicions are formed.

Knowles et al. (2001) (KPT) build a model to test racial preference in police officer decisions of searching motor vehicles. Their key argument is that if there is no racial bias and police officers have the same searching cost regardless of race, then the expected return of searching across different races should be equal. Their data, consisting of 1,590 observations, includes all motor vehicle searches on Interstate 95 in Maryland from January 1995 to January 1999. From their data, black driver's vehicles are searched more frequently than white driver's vehicles (63% versus 29%), but the success rate of finding drugs is equal for both groups.

They conclude that police officers treat all drivers equally. If the purpose of stopping vehicles is to search for large amount of drugs (i.e., excluding drivers who carry small amount of drugs), the success rate of finding drugs among black drivers is higher. This implies discrimination against white and Hispanic drivers in favor of black drivers. The research only examines police officer decisions in searching cars and assumes that the costs of searching cars of any race are the same to all police officers. Moreover, the authors assume that race is the only driver characteristic that influences police officer discrimination. Nevertheless, Blalock et al. (2011), Anbarci and Lee (2014), and Engel and Calnon (2004) show that police officer decisions are influenced by other characteristics of drivers such as gender, age, and resident status as well. In addition, Barbe and Horrace (2012) conclude that the data used in Knowles et al. (2001) cannot provide accurate evidence on racial profiling. They point out that Maryland police officer stop and search decisions were varied and affected by several memoranda signed during that period.

Sanga (2009), using the same model and methodology as in Knowles et al. (2001) but with a larger sample of Maryland drivers from 1995 to 2006 and including location fixed effects, reconsiders the findings of Knowles et al. (2001). He shows that black and white drivers are searched at the same rate but Hispanic drivers are searched more frequently. Examining all searches along I-95, he concludes that there is a significant large discrimination against Hispanic drivers but police officers treat black and white drivers equally. However, when considering all searches by Maryland police officers, he finds that the success rate of finding contraband among white drivers is higher than among black and Hispanics drivers. In other words, there is discrimination against black and Hispanics drivers.

Dharmapala and Ross (2004) generalize the KPT model by taking into account the fact that police officers may not observe all potential offenders. Thus, there is a fraction of drivers who are not deterred even if they carry contraband. The authors include two levels of offense severity: carrying a small or large quantity of drugs. Using the same Interstate 95 data of Maryland from January 1995 to January 1999 as Knowles et al. (2001), they find that how black drivers are treated compared to white drivers depends on the samples and whether drivers choose to carry drugs and contraband. When drivers who carry a small amount of contraband choose to commit with certainty and other drivers randomize between not carrying contraband and carrying large amounts, police officers are more lenient with black drivers. This conclusion holds when considering the full sample, a sub-sample including only male police officers, or a sub-sample including only female police officers. In contrast, when drivers who carry large amounts of contraband will commit with certainty and other drivers randomize between not committing and carrying small amounts, in the sample including only female police officers, the authors find that female police officers discriminate against black drivers.

Anwar and Fang (2006) assume that police officers, before making any decisions on vehicle searches, observe several characteristics of drivers that are correlated with the likelihood that drivers carry drugs. However those characteristics are unknown to drivers. The authors use traffic stop data from the Florida Highway Patrol between January 2000 and November 2001, controlling for not only race but also other characteristics of drivers and police officers that may influence police officer decisions such as age, in-state status, the time when drivers were pulled over, and the rank of police officers. Their insight is that if there is no racial bias, the search rates and success rates of finding contraband should be independent of driver race and in the same rank order according to police officer race. They fail to reject the hypothesis that there is no racial discrimination. However, they are able to show that search rates and success rates vary across police officer race.

Alternatively, Antonovics and Knight (2009) assume that driver characteristics which influence police officer decisions are known to both drivers and police officers. The authors argue that if police officers have no racial preference, the search rates across driver races will be independent of police officer race, given that police officers have the same search costs for drivers of different race. From data on traffic stops in Boston for the two-year period starting in April 2001, they find that police officers are more likely to search vehicles of drivers whose race is different from theirs. However, the assumption that the cost difference of searching white and black drivers are the same to white and black officers may not be hold. In addition, the dependent variable is whether a police officer conducts a search. Therefore, we only know the difference in probability of being searched among drivers of the same race with other groups.

Higgins et al. (2011) examine if driver race and/or ethnicity influence police officer decisions on search using propensity score matching. Analyzing a sample of 3,568 observations from the 2005 Police-Public Contact Survey, the authors find that black drivers are more likely to be searched than white drivers. However, there is no difference in search rates between white drivers and Hispanic drivers. The authors therefore conclude that race is a causal factor in police officer decisions to search.

Ridgeway (2006) uses propensity score matching in order to investigate the effect of driver race on traffic stop outcomes. The author constructs a weighted comparison group whose distribution of traffic stop features matches the distribution of traffic stop features of black drivers and then compares the stop outcomes between the two groups. Traffic stop features include the location of the stop, gender and age of the driver, if the driver is a resident of Oakland, and the reason for the stop. The data consists of 7,607 traffic stops made by the Oakland Police Department, California from June

15, 2003 to December 30, 2003. He finds that there is no significant racial preference in the citation rate or consent search rate but police officers are, respectively, 6 and 2.5 times more likely to pat search and probable cause search a black driver than a white driver. However, for consent searches, only those cases in which police officers request for search and the drivers give consent were recorded. This fact can lead to bias since the consent rate may be different across race. Regarding duration of stops, he finds that black drivers are less likely than non-black drivers or white drivers from the comparison group to be stopped for less than 10 minutes.

Using propensity score matching can help compare two groups of dissimilar features of stops. Nevertheless, there are several unobserved factors from police department such as police department policies or structure that might influence police officer discretionary decisions but are not included in the analysis. These factors can be taken into account when using police department fixed effects method. Moreover, the conclusion of racial disparity in the duration of stops may be inconclusive. Investigating groups of drivers whose stop lasted less than 10 minutes puts equal weight on stops that last 1 minute and 9 minutes.

4.3 Illinois stop and search data

Following Public Act 096-0658, since January 2004, state and local police agencies in Illinois have been required to record and submit data relative to traffic stops made within their jurisdiction to the Illinois Department of Transportation. Every law enforcement agency has to compile the data collected from July to December to submit by March 1 and from January to June to submit by August 1.

Accordingly, police officers record name, address, gender, and race of drivers who are stopped from driver license. In addition, police officers use their best judgment in order to identify driver race from six categories: White, black, Indian American, Hispanic, Asian, and Native Hawaiian. Regarding the stop, police officers record date, location, and the time at which the stop begins and ends. The model and year of the stopped vehicles as well as the violation that lead to the stop are also recorded. Regarding police officer identification, we know the name and the agency code of the police agency at which the police officer works.

In 2012, 923 police agencies in Illinois submitted traffic stop data. The total numbers of traffic stops made and recorded in Illinois in 2012 were 2,132,006. Moreover, in 2012, the Illinois population over 18 years old was 9,805,562; thus, on average 1 in every 5 people above the driving age in Illinois has been stopped by a police officer.

Traffic stops can occur as the result of violating Illinois traffic regulations, but does not include traffic accidents. Traffic stops are due to moving violation (70.09%), equipment violation (18.68%), license plate violation (10.06%), and commercial vehicle (1.17%). Commercial vehicle violation indicates violations of rules and regulations related to commercial vehicles that are not categorized as other violations listed. Moving violations are categorized into speeding violation (58.24%), traffic sign or signal violation (16.02%), lane violation (8.29%), seat belt violation (5.48%), and other violations (11.34%). Of all traffic stops in 2012, 53.59% result in tickets, 27.94% result in written warnings, and 18.47% result in verbal warnings.

Regarding outcomes of stop and search, we know if a police officer requests a vehicle, driver, or passenger search; and, if so, if the search is by consent or other means. We also know if the driver, vehicle, or passenger searches are conducted and if drug, drug paraphernalia, alcohol, weapons, or stolen property is found in the vehicle or on the driver or passenger. In addition, we have information on if a police dog performs search; and, if so, whether the police dog finds contraband/drugs. The amount of drugs found by either police officers or a police dog is presented in categorical variables.

We collect sunset and sunrise times in Illinois from Illinois Department of Natural Resources. Those times are adjusted in order to reflect the correct time on all dates of the year, including winter-summer weather, Standard Time, and daylight saving time. We merge the data with our Illinois traffic stops using date of the year.

We drop several observations for the following reasons. First, we drop 649 duplicated observations. Second, we do not include 11,844 drivers whose recorded race is either American Indian (0.29%) or Native Hawaiian (0.26%). Taking into account of missing values in covariates, we have a final sample of 1,997,186 observations.

4.4 Illinois police officer discretionary decisions

4.4.1 Search and success rate analysis

In this subsection, we use KPT's model to examine if police officers discriminate against any groups of drivers. If the average success rates of finding contraband are different across driver characteristic, it indicates that driver characteristics influences police officer discretionary decisions. In this section, we consider not only the effect of driver race as in the KPT model but also other characteristics of drivers such as gender, age, and resident status.

KPT model

KPT assume a continuum of drivers characterized by (c, r). The value of $c \in [0, 1]$ represents all other characteristics other than the race of a driver. The value of c is observable to police officers but is not recorded in the data. The value of $r \in A, H, B, W$ indicates the race of the driver with B representing a black driver, H representing a Hispanic driver, W representing a white driver, and A representing an Asian driver. The authors assume that each driver considers the probability of being searched when deciding whether to carry contraband. A driver will receive a payoff of 0 if he/she does not carry contraband. If a driver of type (c, r) carries contraband, he/she will receive a payoff of $-j(c,r)$ if he/she is searched and $v(c,r)$ if he/she is not searched. Each police officer observes driver type (c,r) and decides whether to search with probability $\gamma(c,r) \in [0,1]$. The objective of the police officer is to maximize the expected benefit minus the cost of searching a vehicle. The marginal cost of searching a driver of race r is $t_r \in (0,1)$. The benefit of successful search is normalized to 1.

The expected payoff of a driver from carrying contraband is

$$\gamma(c,r)[-j(c,r)] + [1-\gamma(c,r)]v(c,r) \tag{4.1}$$

A driver will choose to carry contraband if his/her expected payoff is positive. When the expected payoff is equal to zero, the driver is willing to randomize between carrying and not carrying contraband. Let $P(G|c,r)$ indicate the probability that the police officer finds driver of type (c,r) carrying contraband. A police officer will choose the probability of searching a driver of type (c,r) to maximize his expected benefit

$$\max_{\gamma} \sum_{r} \int [P(G|c,r) - t_r]\gamma(c,r)f(c|r)dc \tag{4.2}$$

If $P(G|c,r) - t_r > 0$, officers will choose to search for contraband with certainty, probability $\gamma(c,r) = 1$. If $P(G|c,r) - t_r < 0$, officers will choose not to search for contraband, the probability $\gamma(c,r) = 0$. If $P(G|c,r) = t_r$, the officer will randomize between searching and not searching a driver of type (c,r). If an officer has no race preference, the marginal cost of searching will be equal across races ($t_r = t$).

In equilibrium, officers will search when drivers are indifferent of carrying contraband and probability of finding drugs is equal to marginal cost of search:

$$\gamma^*(c,r) = \frac{v(c,r)}{v(c,r) + j(c,r)} \tag{4.3}$$

$$P^*(G|c,r) = t \tag{4.4}$$

The proportion of drivers who are found carrying contraband after search can be calculated by:

$$D(r) = \int P^*(G|c,r)\frac{\gamma^*(c,r)f(c|r)}{\int \gamma^*(s,r)f(s|r)ds}dc \tag{4.5}$$

Substitute $P^*(G|c,r) = t$, we get $D(r) = t$ for all r.

This result suggests that if police officers do not express racial preference on their discretionary decisions, the average success rate of finding drugs or contraband should be equal across races. If the success rate is lower for any group of drivers, it suggests police officers are stricter with that group than with any other group.

An analysis from using search and success rate

We apply the insights from the KPT model in order to test if the probability of finding contraband is equal across driver characteristics in Illinois. Table 4.1 presents the summary statistics of all variables used in analysis (column 1). There are 96,222 stops that lead to searches. Among those searches conducted, 19,917 (20.5%) are for drivers aged 16 to 21, 36,468 (37.9%) for drivers aged 22 to 30, 6,399 (6.65%) for drivers aged 51 to 64, 1,058 (1.11%) for drivers older than 65, and the remaining 32,380 (33.84%) cases are searches of drivers aged 31 to 50. Male drivers are more likely to be searched than female drivers (73,514 searches (76.4%) compared with 22,708 searches (23.6%)). Of the 96,222 searches, 45,897 (47.7%) are performed on white drivers, 29,251 (30.4%) on black drivers, 20,206 (21%) on Hispanic drivers, and 900 (0.94%) on Asian drivers. Most of the stops are performed at night (58,502 searches, 60.8%). Police officers find contraband/drugs in 21,649 cases (22.5%).

In the next columns, we present the summary statistics for subgroups of drivers of their own race and their gender. Drivers aged 22-30 are stopped at the highest rate compared with drivers of other age groups, regardless of the race. Across age group, female and male drivers are stopped at similar rates. Regardless of gender, white drivers are more likely to be stopped than drivers of other races.

Table 4.2 presents the success rates defined as the number of drivers who are searched and found with drugs/contraband out of the number of drivers who are searched across race, gender, age groups, and time of search. It also shows the success rate when conducting from three different forms of search: vehicle, driver and passenger, and police dog. When the success rate of a group is lower than other groups, it indicates that police officers keep searching that group given that the probability of finding drugs from that group is low. It suggests that police officers are stricter/discriminate against that group. Table 4.3 provides the p-values when conducting the Pearson χ^2 test to test if the success rate is equal across groups.

We find that 26.3% of white drivers are searched and found with either contraband or drugs. The corresponding figures for black, Hispanic, and Asian drivers are 22.8%, 13.6%, and 17.5%, respectively. The p-values when comparing these proportions across race are less than 0.001. It suggests that driver race influences police officer discretionary decisions. In particular, police officers discriminate against Hispanic and Asian drivers.

The findings are consistent when examining a smaller sample of drivers who were conducted the same type of search. Except among groups of drivers conducted a police dog search, we find that the success rate of Hispanic drivers is higher than that of Asian drivers. It suggests that Asian drivers are treated stricter than Hispanic drivers in police dog search.

In panel 2 and 3 of the table, we consider police officer decisions across race of female and male drivers. The results are consistent with the previous findings in panel 1. Driver race influences police officer decisions. There are only two exceptions. We find that among sample of female drivers whose vehicles are searched, 20.6% of white drivers are found with drugs/contraband while the corresponding number for Asian drivers is 14.7%. However, we cannot reject the hypothesis that police officers treat Asian and white female drivers equally. Similarly, within sample of female drivers who are conducted a police dog search, we cannot reject the hypothesis that white female and black drivers drivers are treated equally.

When examining success rates across gender, we find that police officers are less likely to find contraband or illegal property from female drivers. This suggests that police officers discriminate against female drivers, which runs contrary to the long-standing belief. However, Blalock et al. (2011) also find that female drivers are more likely to receive tickets than male drivers in three out of five locations that they examine. In the sample of drivers who are conducted a police dog search, we find that proportions of female and male drivers found with drugs are almost equal (55.7% and 53.9%, respectively). However, the p-value is 0.275; we cannot reject the hypothesis that police officers treat male and female drivers equally.

Across age groups, we find that the older a driver is, the stricter a police officer is more likely to be. The success rate of finding drugs/contraband is highest for group of young drivers from 16 to 21 years old and lowest for senior drivers older than 65.[3]

The success rate in daytime is lower than at night, which suggests that police officers are stricter with drivers who are stopped during the day. However, the reason may be that drivers who carry drugs/contraband usually drive at night. Therefore, the probability of finding drugs/contraband is higher at night than during the day. Grogger and Ridgeway (2006) compare the distribution of drivers being pulled over during day and night. They argue that if police officers have no racial prejudice then

[3]This finding is opposite to conventional belief that police officers are more lenient to senior drivers.

the distribution of the race of drivers who are pulled over during the day and the night should be the same. Using data collected in Oakland, California, they conclude that there is no racial discrimination. However, using the same data and the propensity score method, Ridgeway (2006) found that white drivers are more likely to be ticketed.

While examining the success rate of finding drugs/contraband is a good way to measure police officer discrimination, there are still concerns. First, the model does not control for other characteristics of drivers when comparing the success rate of finding drugs. For example, while the results show the difference in success rates of finding contraband between white and black drivers, it indicates that police officers discriminate on race. However, it may exist because police officers discriminate on other driver characteristics. Second, the variety in police department policies may lead to differences in stop and search patterns. In some dangerous areas, which happen to have a higher density of minority people, the police department may have a strict policy that requests police officers to conduct stop and search more frequently than in other areas, which can effectively lower the success rate, but may not mean that police officers discriminate.

4.4.2 Illinois police officer discretionary decisions on duration of stops

Econometric model

Tests of police officer discretionary decisions typically compare decisions of stop and search, decisions regarding the issuing of tickets, and the amount of fine. All of these decisions immediately affect the situation at hand and lead to further actions. If a driver thinks the decision is incorrect or made in error, he/she may choose to appeal. Since police officer performance can be partially affected, police officers may consider the consequences of their decisions before making decisions on each traffic stop/search.

Another indicator that can be used to measure police officer discretion is the duration of stops. Since drivers do not pay attention to the length of stops, they do not notice if there is any difference in police officer intention on stop duration. In this section, we focus on the duration of stops and investigate if driver characteristics influence police officer discretionary decisions regarding the duration of stops. In addition, we concern that each police department may have some unobserved different policies and benchmarks to measure the performance of police officer, which, in turn, will influence police officer decisions within each department. We deploy OLS regression with police agency fixed effects to take into account these omitted unobservable characteristics.[4]. In addition, we use cluster robust standard error over the zip code where a driver is stopped to take into account that the model errors for each police officer may be correlated within the same location.

$$Duration_{itp} = \beta_0 + \beta_1 Driver_{itp} + \beta_2 X_{itp} + \beta_3 Pol_p + \varepsilon_{it} \tag{4.6}$$

Dependent variable ($Duration_{itp}$) is the duration (in minutes) of a traffic stop in which police officer in police agency p stopped driver i.

$Driver_i$ includes characteristics of driver i such as dummy variables for driver race and gender, whether a driver is black, Hispanic, or Asian (White drivers as the control group), and female driver. It also includes driver age group dummies: aged less than or equal to 21, aged 22-30, aged 51-64, and aged equal to or greater than 65 (drivers aged 31-50 as the reference group).

X_t includes whether driver i is stopped at night and at what month of 2012 and whether it is end of the month. In the data, police officers record time at which drivers were stopped. We create a dummy variable, night, equal 1 if a police officer

[4]Using the Hausman test, we reject the hypothesis that the police agency effects are adequately modeled by the random-effects model.

stops a vehicle before sunrise or after sunset of that day and equal 0 otherwise. We also include interaction between black driver and night to check whether black drivers were more likely to be stopped during the day than at night. Dummy variables indicating the type of violations: equipment, license/registration, commercial vehicle, and moving violations are also included. Pol_p indicates the police agency which the police officer works for.

An analysis of police officer discretionary decisions in duration of stops

Table 4.4 gives summary statistics of the variables used in analysis with the full sample and samples of drivers who received citations, written warnings, or stop card (verbal warning) separately. Moreover, samples only include drivers from whom police officers do not conduct any search on either vehicle, driver, passenger, or police dog search. Of 1,997,186 drivers who are stopped, 1,046,724 (52.4%) drivers are issued tickets, 578,214 (28.95%) drivers with written warnings, and 372,249 (18.64%) drivers with stop cards. On average, each traffic stop takes 11.03 minutes. If a driver receives a ticket, it will take him an average of 12 minutes and 30 seconds. The corresponding numbers for drivers receiving a written warning and a stop card are 10 minutes 22 seconds and 7 minutes 52 seconds, respectively.

Among drivers who are stopped, 14.7% are from 16 to 21 years old, 27.2% from 22 to 30, 14.9% from 51 to 64, only 4.51% are older than 65 years old, and 37.4% are female. White drivers represent 67.51% of all stopped drivers, while the proportions for black, Asian, and Hispanic drivers are 17.9%, 2.99%, and 11.6%, respectively. 43.2% of stopped drivers are stopped at night.

Table 4.5 presents the results from regressing duration of stops on driver characteristics, type of violations, month of year when the driver is stopped, with police agency fixed effects. For the samples of drivers who receive tickets, written warnings, or stop cards only, most of the estimates are consistent in terms of signs and significance level. When examining the full sample, we find that police officers are more lenient with old drivers and stricter with young drivers than drivers aged 31 to 50 years old. Drivers whose ages are from 16 to 21, on average, are stopped 24 seconds longer while senior drivers are stopped 41 seconds shorter than middle-aged drivers aged 31-50.

Female drivers are stopped an average of 48 seconds shorter than male drivers. In addition, police officers are more likely to hold black and Hispanic drivers 53 and 93 seconds longer than white drivers, respectively. Being stopped at night tends to take 21 seconds longer than at other times of the day.

Regarding violations, drivers who are stopped for equipment violations take 20 seconds shorter than for moving violations. Police officers stop drivers with license/registration violations and commercial vehicle violations 41 seconds and 14 minutes 30 seconds longer than drivers with moving violations, respectively. Part of the explanation may be that commercial driver violations such as heavy vehicles will take time to verify the violation as well as the fine and the solution. The explanation/violation must also exist in related to the third party (e.g. the company that the driver works for).

Tables 4.6 presents the summary statistics of variables used in analysis with samples of stops due to moving violation, equipment violation, license violation, and commercial vehicle, separately. On average, drivers are stopped 10 minutes 48 seconds for a moving violation, 10 minutes 41 seconds for a equipment violation, 11 minutes and 19 seconds for a license/registration violation, and 26 minutes and 35 seconds for a commercial vehicle violation. Most stops are for moving violations - 1,405,550 cases (70.38%), equipment violations - 369,937 cases (18.52%), license violations - 197,220 cases (9.87%), and commercial vehicle violations - 24,479 violations

(1.23%). Across violations, young drivers aged 16-21 and aged 22-30, female drivers are less likely to be stopped for commercial vehicle violations (1.08%, 1.14%, and 2.24%, respectively).

Table 4.7 presents the estimates of the effect of driver characteristics on police office decisions of stop duration. We find most of the estimates are consistent in signs and significance levels with the estimates in Table 4.5. On the other hand, although a young driver aged 16-21 will be held for 1 minutes and 50 seconds longer than a driver aged 31-50, for commercial vehicle violation, the estimates of the effect of driver age are not statistically significant for other age groups. It suggests that for commercial vehicle violations, we cannot conclude that driver age influences police officer decisions. We also find that on average Hispanic and black drivers are stopped for longer time than white drivers for every violation. The only noted change in sign is the estimate for Asian drivers when considering the sample of drivers stopped for a moving violation. If an Asian driver is stopped for a moving violation, on average, he/she will be stopped 4 seconds longer than a white driver. For a commercial vehicle violation, an Asian driver is stopped an average of 2 minutes 36 seconds longer than a white driver.

Table 4.8 presents the summary statistics of variables used in analysis with samples of stops for speeding violations, lane violations, seat belt violations, and traffic sign/signal violations. The duration of stop ranges from 10 minutes 7 seconds for traffic sign/signal violation to 11 minutes 32 seconds for lane violations. The majority of stops are for speeding violations (60.85%).

Table 4.9 looks at the sample of drivers who are stopped but not searched for either a speeding violation, a lane violation, a seat belt violation, or a traffic sign/signal violation. We find that Asian drivers are stopped an average of 12 seconds longer when being stopped for speeding violation and 7 seconds longer when being stopped for traffic sign/signal violation than white drivers. However, Asian drivers are stopped an average of 31 seconds shorter than white drivers when being stopped for traffic lane rules. On average, Hispanic and black drivers are stopped longer than white drivers for all violations. The estimated effect of age on the duration of stops are consistent with estimates from the full sample in Table 4.5.

In previous tables, we do not include drivers who were searched since it may take time to conduct a search. Including those drivers may give incorrect estimates for those who are only stopped for traffic violations. Our next analysis will look at drivers who are searched but no contraband/drugs are found.

In Table 4.10, we provide summary statistics for the sample of drivers in which either a vehicle search, a driver search, a passenger search, or a police dog search is conducted and nothing is found. These samples do not include drivers where more than one subject is searched (e.g. both vehicle and driver search). We show that if a police officer conducts a search, the stop will take longer than without a search. On average, it takes 17 minutes and 38 seconds for a vehicle search, 23 minutes 40 seconds for a driver search, 22 minutes 49 seconds for a passenger search, and 22 minutes 46 seconds for a police dog search.

Table 4.11 examines the effect of driver characteristics on duration of stops for the sample of drivers in which either a vehicle, driver, passenger, or a police dog search is conducted and nothing is found. Unexpectedly, it shows that young drivers aged 16-21 are searched an average of 69 seconds fewer than middle-aged drivers in a vehicle search and 4 minutes 28 seconds fewer in a police dog search. The reason may be that after a quick search during which police officers do find nothing suspicious, they will let the young drivers go. However, police officers may presume that middle-aged drivers are more experienced at concealing items. So it may take longer for a police officer to search.

The duration of stop in vehicle search is the shortest for white drivers compared to Hispanic drivers (3 minutes 28 seconds longer), Asian drivers (3 minutes 20 seconds longer), and black drivers (99 seconds longer). However, when conducting a driver search, it takes black and Hispanic drivers an average of 80 seconds and 63 seconds fewer than white drivers, respectively. For police dog search, all the differences are not statistically significant except for Hispanic drivers with the stop duration of 4 minutes and 8 seconds longer than white drivers. What may partially explain this is that black and Hispanic drivers are more likely not to give police officers consent to conduct a driver search. So police officers may conduct a shorter driver search for black and Hispanic drivers.

We find that night stops lasts longer than day stops. It may be that it is harder to conduct a search at night than during the day because of the lack of light. We also find that stops for equipment violations last are shorter and stops for license/registration violations and commercial vehicle violations are longer than stops for moving violations.

We notice that in one stop, a police officer may conduct multiple searches of vehicle, driver, and passenger, or use police dog search. In Table 4.12, we provide summary statistics for the sample of drivers in which either a vehicle search, a driver search, a passenger search, or a police dog search were conducted and no drugs/contraband was found. This table includes stops that lead to either one or multiple searches. The average length for police dog search increases from 22 minutes and 47 seconds to 27 minutes and 12 seconds. The average length for a vehicle search increases from 17 minutes 38 seconds to 22 minutes.

Table 4.13 presents the effects of driver characteristics on duration of stops. Young drivers aged 16-30 and senior drivers are stopped less time than middle-aged drivers. Perhaps, part of the explanation is that middle-aged drivers may have more experience in hiding drugs/contraband and are more likely to carry them. So it will take police officers longer to search. Unexpectedly, female drivers are stopped longer than male drivers in vehicle search and driver search. It may be that police officers are more lenient with female drivers when making decisions to search. But when police officers decide to search, they will search the vehicles of female drivers as carefully as the vehicle of male drivers.

Police officers stop black, Asian, and Hispanic drivers longer than white drivers in vehicle search, and black and Hispanic drivers longer than white drivers in a passenger search. But the differences in duration of stops are smaller than that corresponding in Table 4.11. Hispanic drivers are stopped 8 minutes 9 seconds longer than white drivers in a police dog search. We do not find any evidence of the effect of driver race on duration of stop in sample of driver searches since the estimates are positive but not statistically significant.

Table 4.14 gives summary statistics of covariates used in analysis for three different samples of drivers: searched, searched and no drugs found, and searched and found. Of 96,222 drivers searched, 21,680 drivers (22.53%) are found with drugs/contraband and 74,542 drivers (77.47%) are not found with drugs/contraband. If a search is conducted, it will take, on average, 23 minutes 56 seconds. Of all drivers searched, 20.7% are young drivers aged 16-21, 37.9% drivers aged 22-30, 6.65% drivers aged 51-64, and 1.11% drivers older than 65. White drivers are more likely to be searched than black, Asian, and Hispanic drivers (47.66% versus 30.4%, 0.94%, and 21%, respectively).

Table 4.15 presents the effect of driver characteristics on duration of stops. Most of the estimates are consistent in sign and significance level with the estimates in Tables 4.11 and 4.13. We find that drivers aged 31-50 have the longest stop duration compared to both their younger and older counterparts. This is different from what we find when considering samples that police officers don't conduct searches in Table 4.5. We do not find the different in stop duration between male and female drivers for search conducted and nothing found sample. Within the sample of drivers with found contraband/drugs, female drivers are stopped an average of 53 seconds longer than male drivers. In addition, police officers stop black, Asian, and Hispanic drivers shorter than white drivers. Police officers keep drivers longer for stops at night than at day.

4.4.3 Illinois police officer discretionary decisions on searching, giving ticket and duration of stops - propensity score matching analysis

To identify causal effects with the regression approach, we need to make sure that other characteristics of the treated and control groups, except the treatment, have similar influence on the outcomes. As our hypothesis is whether police officer discretionary decision differs across race, in an experimental settings we can test by looking at police decisions toward randomized-controlled groups which differ in race but are the same in every other aspects. However, Grogger and Ridgeway (2006) shows that police officers stop black drivers at nonequivalent rates during the day and the night. In addition, in this study, we can not do random assignment to treatment and control groups because we can not impose race to a driver. Therefore, it may lead to selection bias problem.

In non-experimental settings, the use of propensity score matching methods to correct for sample selection bias due to observable differences between the treatment and comparison groups has been a preferred approach (Dehejia and Wahba (2002)). Moreover, Becker and Ichino (2002) find that results from using propensity score matching methods are closely equal to the estimates obtained from using randomized experimental. Here, we examine the racial disparity in police officer decisions of stop and search, ticketing, and duration of stop by using propensity score matching method. This approach of using race as a treatment in the propensity score matching method has been used in previous research such as Higgins et al. (2011), Ridgeway (2006), and Higgins et al. (2013) to study racial disparity.

The propensity score matching includes two steps. We first use the logistic regression to find the propensity of receiving treatment which is the probability that the race of the stopped driver is white:

$$P(w) = Pr(w = 1|x) \tag{4.7}$$

where $P(w)$ is the propensity of being white, w is a indicator of being white driver, x includes driver gender and age group, type of violation and an indicator of night stop.

We use kernel propensity score matching to match observations in treatment and control groups. Observations that have similar propensity scores can be expected to have similar values of their observable characteristics. This step ensures that the propensity score distribution is similar across groups. To test for the balance of pretreatment variables given the propensity, first, we divide the sample into 5 equally spaced intervals of propensity score. Second, we test that the mean propensity score is not different for treated and controls. If there is a difference in one interval, we split that interval in half and retest. The step is done and we can continue the next step when the average propensity score of treated and controls does not differ in all intervals. Third, we test that the means of each characteristic do not differ between treated and controls within each interval. We perform t-test to test if the means of each characteristic are significantly different and calculate the standardized bias of characteristics to assess the qualify of matching. If the means differ, the balancing property is not satisfied. Lastly, when the balancing property satisfies, we can estimate the difference in probability of receiving a ticket, being searched, and duration of stop between treated and control groups.

We use the stop and search data of all drivers stopped in zip code 60505 in which the total of stop and search is the highest among other zip codes in Illinois stop and search 2012 data.[5] The sample includes 18,308 stops. We examine police officer discretionary decisions not only between black and white drivers but also between white and Hispanic drivers.

Table 4.16 shows the descriptive statistics of all covariates both before and after using propensity score matching. The first panel includes black and white drivers. The second panel includes Hispanic and white drivers. The third panel includes Asian and white drivers. The first two columns are average value of driver characteristics. The standardized bias values is in column 3 and the p-value from the t-test is in column 4.

From panel 1, we find that black and white drivers are well-matched after using propensity score matching. Before matching, the standardized bias in the covariates among original samples ranges from -11.7% to 11.1%. The p-values in column 4 indicate that the characteristics of white drivers are statistically different from those of black drivers. After performing the propensity score matching, the standard bias decreases, ranging from -3.1% to 4.3% for white and black drivers and there is no significant differences in characteristics between two groups.

Similarly, from panel 2, Hispanic and white drivers are well matched after using propensity score matching. The standardized bias ranges from -21.3% to 24.5% before matching and from -4.2% to 7.2% after matching. We find that the characteristics

[5]We have tried to apply propensity score method with the full sample or county level sample. However, the data that we use here is the largest data set that can be analyzed because of the unequal average propensity score and unbalanced property in steps 2 and 3 for larger samples

indicating drivers aged 51-64 and drivers who stopped for license violations are not well-matched between Hispanic and white drivers. From panel 3, we find that the Asian and white drivers are not well matched after using propensity score matching. The t-test indicates that after using matching, the characteristics of Asian and white drivers are significantly different.

Table 4.17 presents whether there is a racial disparity in police officer decisions on searching, ticketing, and duration of stops. The first 4 columns show the results from the original sample (without propensity score matching) and columns 5 to 8 present results from kernel matching sample (propensity score matching). Compared with the results in columns 3 and 7, we find that the differences get smaller after performing propensity score matching. This finding indicates the need for samples of similar characteristics in order to obtain the exact effect of the treatment on the outcomes.

Propensity score matching result shows that compared to black drivers, white drivers have 0.7 percentage point lower in probability of being searched and 69 seconds shorter in the duration of stop. The probability of receiving a ticket is not statistically different between black and white drivers. It may partially explained by the perception that black drivers are more likely to carry drugs/contraband. Police officers therefore stop and search them at higher rate and for longer time. But there is no difference in probability of receiving a ticket.

Police officers are more lenient toward white drivers than Hispanic drivers. Particularly, white drivers receive 3.6 percentage point lower in the probability of being searched, 7.8 percentage point lower in the probability of receiving a ticket, and 75 seconds shorter in the length of stop. This suggests that police officers discriminate against Hispanic drivers. In addition, we find that white drivers are more likely to receive stop durations which are less than 10 minutes than their counterparts. Our results are consistent with Ridgeway (2006) findings that black drivers are less likely than non-black drivers or white drivers from the comparison group to be stopped for less than 10 minutes. We find that conclusion is also true for white and Hispanic drivers. However, we cannot reject the hypothesis that white and Asian drivers are treated equally.

4.5 Summary

In this study, we examine the influence of driver characteristics on police officer decisions regarding stops, search and duration of stop. We show that more white drivers are stopped and searched than black, Hispanics and Asian drivers. However, the success rates of finding contraband from white drivers are the highest compared to those from drivers of other races. We therefore conclude that police officers are more lenient toward white drivers than black, Hispanic, and Asian drivers. Using police agency fixed-effects model, we also find that white drivers are stopped for shorter time than drivers of other race. In addition, we shows that white drivers receive more favor from police officers in probability of receiving ticket, probability of being searched, and duration of stop.

Police officers are less likely to find contraband from female drivers and old drivers, compared to male drivers and middle-aged drivers, respectively. It suggests that police officers are stricter with female drivers and old drivers. In contrast, using police agency fixed-effects model and clustering over zip-code, we find that police officers are more lenient with female drivers than with male drivers and that police officers are stricter with younger drivers, more lenient with older drivers compared to middle-aged drivers.

In general, this research shows the need to take into account all the factors that might influence police officer decisions. While the KPT model has been commonly used in the literature to investigate police officer discrimination, it only shows the difference between two groups of drivers. However, it cannot certain that the factor considered is the reason of the difference. The reason may come from the difference of other characteristics in two groups. In this research, to control for the heterogeneity, we use two methods: police agency fixed effects model and propensity score matching. The results from both methods are consistent. We find that driver characteristics such as race, gender, and age have statistically significant influence on police officer decisions.

Table 4.1 Summary statistics of variables used in analysis following KPT model

		By race				By gender	
	All	Black	Hispanic	White	Asian	Female	Male
Age 16-21	0.207	0.172	0.192	0.236	0.194	0.208	0.206
	(0.405)	(0.377)	(0.394)	(0.425)	(0.396)	(0.406)	(0.405)
Age 22-30	0.379	0.413	0.392	0.351	0.354	0.379	0.379
	(0.485)	(0.492)	(0.488)	(0.477)	(0.478)	(0.485)	(0.485)
Age 51-64	0.0665	0.0590	0.0371	0.0838	0.0844	0.0612	0.0681
	(0.249)	(0.236)	(0.189)	(0.277)	(0.278)	(0.240)	(0.252)
Age >= 65	0.0111	0.00670	0.00367	0.0170	0.0189	0.0111	0.0111
	(0.105)	(0.0816)	(0.0604)	(0.129)	(0.136)	(0.105)	(0.105)
Female driver	0.236	0.224	0.156	0.281	0.173		
	(0.425)	(0.417)	(0.363)	(0.449)	(0.379)		
White driver	0.477					0.566	0.449
	(0.499)					(0.496)	(0.497)
Black driver	0.304					0.288	0.309
	(0.460)					(0.453)	(0.462)
Asian driver	0.00936					0.00686	0.0101
	(0.0963)					(0.0826)	(0.100)
Hispanic driver	0.210					0.139	0.232
	(0.407)					(0.346)	(0.422)
Night	0.608	0.602	0.556	0.634	0.655	0.601	0.610
	(0.488)	(0.490)	(0.497)	(0.482)	(0.476)	(0.490)	(0.488)
Found	0.225	0.228	0.136	0.263	0.175	0.189	0.236
	(0.418)	(0.420)	(0.343)	(0.441)	(0.380)	(0.392)	(0.425)
Observations	96,222	29,257	20,190	45,874	901	22,731	73,491

Note: Mean of each variable with standard deviation in parentheses.

This table gives summary statistics of variables used in analyzing sample of drivers who were stopped and searched in column 1; from column 2 to 4: subgroups by race; columns 5 and 6: subgroups by gender.

Table 4.2 Proportion of drivers with found contraband

	All	Vehicle	Driver and passenger	Dog
			By race	
White driver	0.263	0.249	0.132	0.586
Black driver	0.228	0.217	0.099	0.528
Hispanic driver	0.136	0.137	0.053	0.361
Asian driver	0.175	0.179	0.065	0.341
			By race for female drivers only	
White driver	0.220	0.206	0.131	0.58
Black driver	0.178	0.177	0.076	0.551
Hispanic driver	0.092	0.097	0.038	0.327
Asian driver	0.128	0.147	0.053	0
			By race for male drivers only	
White driver	0.280	0.266	0.132	0.588
Black driver	0.243	0.229	0.105	0.524
Hispanic driver	0.145	0.144	0.056	0.364
Asian driver	0.185	0.186	0.067	0.385
			By gender	
Male driver	0.236	0.226	0.103	0.539
Female driver	0.189	0.183	0.096	0.557
			By age group	
Age 16-21 years old	0.317	0.298	0.15	0.643
Age 22-30 years old	0.233	0.224	0.1	0.572
Age 31-50 years old	0.177	0.172	0.077	0.46
Age 51-64 years old	0.154	0.148	0.071	0.346
Age >= 65 years old	0.116	0.114	0.073	0.178
			By time of searching	
Day time	0.179	0.176	0.082	0.489
Night time	0.255	0.241	0.113	0.578
Observations	96,222	81,911	68,670	5,499

This table gives the proportion of drivers who were searched and found with contraband, drug, paraphernalia, alcohol, weapon, stolen property, or other illegal property over drivers who were searched. All searches are examined in column 1, while column 2, 3, and 4 only include subgroups of drivers whose vehicle was searched (column 2), either driver or passenger was searched (column 3), and searches which were conducted by police dog (column 4).

Table 4.3 p-value from χ^2 tests

	All (1)	Vehicle (2)	Driver and passenger (3)	Dog (4)
By race				
White, black, Hispanic, and Asian	<0.001	<0.001	<0.001	<0.001
White, black, and Hispanic	<0.001	<0.001	<0.001	<0.001
White and black	<0.001	<0.001	<0.001	<0.001
White and Asian	<0.001	<0.001	<0.001	0.001
White and Hispanic	<0.001	<0.001	<0.001	<0.001
By race for female drivers only				
White, black, Hispanic, and Asian	<0.001	<0.001	<0.001	<0.001
White, black, and Hispanic	<0.001	<0.001	<0.001	0.001
White and black	<0.001	<0.001	<0.001	0.405
White and Asian	0.006	0.1	0.024	0.009
White and Hispanic	<0.001	<0.001	<0.001	<0.001
By race for male drivers only				
White, black, Hispanic, and Asian	<0.001	<0.001	<0.001	<0.001
White, black, and Hispanic	<0.001	<0.001	<0.001	<0.001
White and black	<0.001	<0.001	<0.001	<0.001
White and Asian	<0.001	<0.001	<0.001	0.011
White and Hispanic	<0.001	<0.001	<0.001	<0.001
By gender				
Female and male	<0.001	<0.001	0.024	0.275
By age groups				
Across all age groups	<0.001	<0.001	<0.001	<0.001
Age 16-22 and age 31-50	<0.001	<0.001	<0.001	<0.001
Age above 65 and age 31-50	<0.001	<0.001	0.657	<0.001
By time of searching				
Day time and night time	<0.001	<0.001	<0.001	<0.001

This table gives the p value from the Pearson χ^2 test on the hypothesis that the proportion of being searched and found is the same across subgroups. The proportion values are presented in table 4.2. All searches are examined in column 1, while column 2, 3, and 4 only include subgroups of drivers whose vehicle was searched (column 2), either driver or passenger was searched (column 3), and searches which were conducted by police dog (column 4).

Table 4.4 Summary statistics of variables used in analysis for the whole sample, sample with drivers receiving tickets, written warnings, and stop cards only

	All violation	Ticket	Written warning	Stop card
Duration of stop	11.03	12.50	10.37	7.892
	(9.163)	(10.61)	(6.724)	(6.844)
Age 16-21 years old	0.147	0.150	0.144	0.146
	(0.354)	(0.357)	(0.352)	(0.353)
Age 22-30 years old	0.272	0.289	0.248	0.258
	(0.445)	(0.454)	(0.432)	(0.438)
Age 51-64 years old	0.149	0.135	0.168	0.159
	(0.356)	(0.342)	(0.374)	(0.365)
Age >= 65 years old	0.0451	0.0348	0.0571	0.0556
	(0.208)	(0.183)	(0.232)	(0.229)
Female driver	0.374	0.366	0.386	0.376
	(0.484)	(0.482)	(0.487)	(0.484)
Black driver	0.179	0.188	0.147	0.204
	(0.384)	(0.391)	(0.355)	(0.403)
Asian driver	0.0299	0.0323	0.0273	0.0268
	(0.170)	(0.177)	(0.163)	(0.162)
Hispanic driver	0.116	0.132	0.0827	0.123
	(0.320)	(0.338)	(0.275)	(0.328)
Stopped at night	0.432	0.356	0.493	0.549
	(0.495)	(0.479)	(0.500)	(0.498)
End of month	0.276	0.275	0.275	0.279
	(0.447)	(0.446)	(0.446)	(0.449)
Black driver * Night	0.0873	0.0785	0.0828	0.119
	(0.282)	(0.269)	(0.276)	(0.324)
Equipment violation	0.185	0.125	0.230	0.285
	(0.388)	(0.331)	(0.421)	(0.451)
License/Registration	0.0987	0.0955	0.0952	0.113
	(0.298)	(0.294)	(0.294)	(0.317)
Commercial Vehicle	0.0123	0.00646	0.0174	0.0206
	(0.110)	(0.0801)	(0.131)	(0.142)
Observations	1,997,186	1,046,724	578,214	372,248

Note: Mean of each variable with standard deviation in parentheses.

This table gives summary statistics of variables used in analyzing all traffic stops in column 1; sample of drivers who received ticket citation in column 2; receiving written warning in column 3; receiving stop card in column 4. Only cases in which police officers did not conduct a search are examined.

Table 4.5 Police officer discretionary decisions on length of stops for full sample and samples of drivers receiving tickets, written warnings, and stop cards only

(a) Driver characteristics

	All violation	Ticket	Written warning	Stop card
Age 16-21	0.407***	0.173***	0.183***	0.502***
	(0.026)	(0.036)	(0.028)	(0.039)
Age 22-30	0.417***	0.307***	0.106***	0.288***
	(0.020)	(0.027)	(0.020)	(0.030)
Age 51-64	-0.393***	-0.366***	-0.039*	-0.155***
	(0.021)	(0.033)	(0.023)	(0.029)
Age >= 65	-0.678***	-0.401***	-0.187***	-0.224***
	(0.033)	(0.054)	(0.032)	(0.048)
Female driver	-0.596***	-0.603***	-0.435***	-0.296***
	(0.018)	(0.028)	(0.021)	(0.023)
Black driver	0.876***	1.392***	0.133***	0.326***
	(0.048)	(0.073)	(0.043)	(0.061)
Asian driver	-0.012	-0.048	-0.110***	-0.070
	(0.033)	(0.051)	(0.037)	(0.060)
Hispanic driver	1.545***	2.170***	0.437***	0.021
	(0.081)	(0.115)	(0.036)	(0.078)
Observations	1,997,186	1,046,724	578,214	372,248

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Other characteristics

	All violation	Ticket	Written warning	Stop card
Night	0.355***	1.452***	0.105***	0.179***
	(0.034)	(0.065)	(0.031)	(0.037)
End of month	-0.018	-0.004	-0.016	-0.035
	(0.014)	(0.024)	(0.017)	(0.026)
Black * Night	-0.229***	-0.472***	-0.010	-0.076
	(0.044)	(0.077)	(0.054)	(0.059)
Equipment violation	-0.331***	0.779***	0.312***	-0.062*
	(0.033)	(0.057)	(0.026)	(0.032)
License/Registration	0.677***	1.378***	0.210***	0.170***
	(0.035)	(0.052)	(0.027)	(0.036)
Commercial Vehicle	14.596***	13.955***	20.193***	11.183***
	(0.258)	(1.031)	(0.313)	(0.153)
Observations	1,997,186	1,046,724	578,214	372,248

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows results of regressing duration of stop on variables (shown in table) and controlling for month in which traffic stop was made with police agency fixed-effect and cluster over location zip code where the driver was stopped for sample of all traffic stops in column 1; sample of drivers who received ticket citation in column 2; receiving written warning in column 3; receiving stop card in column 4. Only cases in which police officers did not conduct a search are examined.

Table 4.6 Summary statistics of variables for samples of drivers violating moving, equipment, license, or commercial vehicle rules

	Moving	Equipment	License	Commercial vehicles
Duration of stop	10.80	10.69	11.32	26.58
	(8.650)	(9.064)	(9.512)	(18.32)
Age 16-21 years old	0.146	0.177	0.120	0.0108
	(0.353)	(0.382)	(0.325)	(0.103)
Age 22-30 years old	0.262	0.297	0.313	0.114
	(0.440)	(0.457)	(0.464)	(0.318)
Age 51-64 years old	0.155	0.132	0.122	0.293
	(0.362)	(0.338)	(0.327)	(0.455)
Age >= 65 years old	0.0506	0.0328	0.0297	0.0432
	(0.219)	(0.178)	(0.170)	(0.203)
Female driver	0.389	0.339	0.373	0.0224
	(0.488)	(0.473)	(0.484)	(0.148)
Black driver	0.165	0.206	0.243	0.110
	(0.371)	(0.405)	(0.429)	(0.313)
Asian driver	0.0333	0.0238	0.0187	0.0145
	(0.179)	(0.153)	(0.136)	(0.120)
Hispanic driver	0.109	0.136	0.121	0.178
	(0.312)	(0.343)	(0.326)	(0.383)
Stopped at night	0.387	0.642	0.392	0.147
	(0.487)	(0.479)	(0.488)	(0.354)
End of month	0.278	0.279	0.248	0.298
	(0.448)	(0.448)	(0.432)	(0.457)
Black driver * Night	0.0719	0.140	0.106	0.0216
	(0.258)	(0.347)	(0.308)	(0.145)
Observations	1,405,550	369,937	197,220	24,479

Note: Mean of each variable with standard deviation in parentheses.

This table gives summary statistics of variables used in analyzing sample of drivers who were stopped because of moving violations in column 1; equipment violations in column 2; license violations in column 3; and commercial vehicles in column 4. Only cases in which police officers did not conduct a search are examined.

Table 4.7 Police officer discretionary decisions on length of stops for samples of drivers with violating moving, equipment, license, and commercial vehicle rules

(a) Driver characteristics

	Moving	Equipment	License	Commercial vehicles
Age 16-21	0.471***	0.215***	0.303***	1.828*
	(0.027)	(0.046)	(0.070)	(1.010)
Age 22-30	0.476***	0.230***	0.397***	0.510
	(0.022)	(0.038)	(0.051)	(0.358)
Age 51-64	-0.421***	-0.398***	-0.242***	-0.332
	(0.022)	(0.047)	(0.064)	(0.238)
Age >= 65	-0.658***	-0.791***	-0.809***	0.422
	(0.034)	(0.080)	(0.105)	(0.694)
Female driver	-0.552***	-0.624***	-0.492***	-2.734***
	(0.021)	(0.031)	(0.042)	(0.708)
Black driver	0.866***	0.656***	1.229***	-0.048
	(0.049)	(0.097)	(0.087)	(0.381)
Asian driver	0.069*	-0.122*	-0.016	-2.605***
	(0.036)	(0.073)	(0.146)	(0.698)
Hispanic driver	1.524***	1.285***	1.784***	1.851***
	(0.093)	(0.081)	(0.109)	(0.322)
Observations	1,405,550	369,937	197,220	24,479

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Other characteristics

	Moving	Equipment	License	Commercial vehicles
Night	0.703***	-0.759***	0.220***	-4.000***
	(0.039)	(0.052)	(0.056)	(0.368)
End of month	-0.037**	-0.012	0.146***	-0.747***
	(0.015)	(0.032)	(0.047)	(0.245)
Black * Night	-0.250***	-0.039	-0.199*	-0.126
	(0.048)	(0.098)	(0.116)	(0.756)
Observations	1,405,550	369,937	197,220	24,479

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows results of regressing duration of stop on variables (shown in table 4.7a and 4.7b) and controlling for month in which traffic stop was made with police agency fixed-effect and cluster over location zip code where the driver was stopped for sample of drivers who were stopped because of moving violations in column 1; equipment violations in column 2; license violations in column 3; and commercial vehicles in column 4. Only cases in which police officers did not conduct a search are examined.

Table 4.8 Summary statistics of variables for samples of drivers violating speeding, lane, seat belt, or traffic sign/signal rules

	Speeding	Lane violation	Seat belt	Traffic sign/signal
Duration of stop	10.66	11.54	10.17	10.12
	(7.923)	(10.37)	(9.426)	(7.553)
Age 16-21 years old	0.147	0.139	0.148	0.140
	(0.354)	(0.346)	(0.355)	(0.347)
Age 22-30 years old	0.264	0.237	0.291	0.247
	(0.441)	(0.425)	(0.454)	(0.431)
Age 51-64 years old	0.151	0.184	0.142	0.167
	(0.358)	(0.387)	(0.349)	(0.373)
Age >= 65 years old	0.0461	0.0746	0.0484	0.0591
	(0.210)	(0.263)	(0.215)	(0.236)
Female driver	0.405	0.344	0.292	0.398
	(0.491)	(0.475)	(0.455)	(0.489)
Black driver	0.147	0.187	0.180	0.190
	(0.354)	(0.390)	(0.384)	(0.392)
Asian driver	0.0324	0.0403	0.0217	0.0401
	(0.177)	(0.197)	(0.146)	(0.196)
Hispanic driver	0.0879	0.137	0.122	0.149
	(0.283)	(0.343)	(0.328)	(0.356)
Stopped at night	0.362	0.587	0.217	0.414
	(0.480)	(0.492)	(0.412)	(0.493)
End of month	0.277	0.278	0.297	0.277
	(0.447)	(0.448)	(0.457)	(0.447)
Black driver * Night	0.0590	0.117	0.0500	0.0871
	(0.236)	(0.321)	(0.218)	(0.282)
Observations	855,284	112,410	79,787	225,861

Note: Mean of each variable with standard deviation in parentheses.

This table gives summary statistics of variables used in analyzing sample of drivers who stopped for moving violations: speeding violation in column 1; lane violation in column 2; seat belt violation in column 3; traffic sign/ signal in column 4. Only cases in which police officers did not conduct a search are examined.

Table 4.9 Police officer discretionary decisions on length of stops for samples of drivers who violate speeding, lane, seat belt, traffic sign/signal rules

(a) Driver characteristics

	Speeding	Lane violation	Seat belt	Traffic sign/signal
Age 16-21	0.535***	0.004	0.387***	0.574***
	(0.029)	(0.102)	(0.104)	(0.056)
Age 22-30	0.483***	0.504***	0.310***	0.525***
	(0.028)	(0.083)	(0.074)	(0.042)
Age 51-64	-0.342***	-0.670***	-0.282***	-0.453***
	(0.024)	(0.083)	(0.082)	(0.040)
Age >= 65	-0.536***	-1.178***	-0.554***	-0.717***
	(0.045)	(0.099)	(0.096)	(0.058)
Female driver	-0.480***	-0.750***	-0.058	-0.427***
	(0.024)	(0.056)	(0.089)	(0.033)
Black driver	0.806***	0.166	0.873***	0.659***
	(0.050)	(0.116)	(0.162)	(0.089)
Asian driver	0.194***	-0.514***	0.270	0.118*
	(0.048)	(0.110)	(0.169)	(0.062)
Hispanic driver	1.479***	1.274***	0.793***	1.070***
	(0.118)	(0.113)	(0.102)	(0.084)
Observations	855,284	112,410	79,787	225,861

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Other characteristics

	Speeding	Lane violation	Seat belt	Traffic sign/signal
Night	0.739***	0.595***	0.701***	0.310***
	(0.049)	(0.081)	(0.109)	(0.047)
End of month	-0.026	-0.097	-0.076	-0.010
	(0.018)	(0.065)	(0.065)	(0.036)
Black * Night	-0.117*	-0.310**	-0.290	-0.027
	(0.062)	(0.135)	(0.205)	(0.106)
Observations	855,284	112,410	79,787	225,861

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows results of regressing duration of stop on variables (shown in table) and controlling for month in which traffic stop was made with police agency fixed-effect and cluster over location zip code where the driver was stopped for sample of drivers who stopped for moving violations: speeding violation in column 1; lane violation in column 2; seat belt violation in column 3; traffic sign/ signal in column 4. Only cases in which police officers did not conduct a search are examined.

Table 4.10 Summary statistics of variables for samples of drivers that police officers conduct a vehicle, driver, passenger or police dog search

	Vehicle	Driver	Passenger	Police dog
Duration of stop	17.63	23.67	22.82	22.76
	(17.00)	(21.40)	(20.66)	(16.86)
Age 16-21	0.204	0.131	0.245	0.177
	(0.403)	(0.338)	(0.430)	(0.382)
Age 22-30	0.326	0.381	0.369	0.327
	(0.469)	(0.486)	(0.483)	(0.469)
Age 51-64	0.104	0.0723	0.0601	0.0871
	(0.305)	(0.259)	(0.238)	(0.282)
Age >= 65	0.0283	0.00825	0.0110	0.0241
	(0.166)	(0.0904)	(0.104)	(0.154)
Female driver	0.344	0.231	0.389	0.212
	(0.475)	(0.421)	(0.488)	(0.409)
Black driver	0.190	0.302	0.393	0.223
	(0.392)	(0.459)	(0.489)	(0.416)
Asian driver	0.0112	0.00945	0.00761	0.0241
	(0.105)	(0.0968)	(0.0870)	(0.154)
Hispanic driver	0.115	0.321	0.118	0.153
	(0.319)	(0.467)	(0.322)	(0.360)
Stopped at night	0.547	0.538	0.605	0.507
	(0.498)	(0.499)	(0.489)	(0.500)
End of month	0.267	0.277	0.263	0.290
	(0.443)	(0.447)	(0.441)	(0.454)
Black * Night	0.107	0.167	0.254	0.110
	(0.309)	(0.373)	(0.435)	(0.313)
Equipment violation	0.215	0.206	0.330	0.243
	(0.411)	(0.404)	(0.470)	(0.429)
License/Registration	0.132	0.166	0.147	0.0737
	(0.339)	(0.372)	(0.354)	(0.262)
Commercial Vehicle	0.00527	0.00213	0.00169	0.0456
	(0.0724)	(0.0461)	(0.0411)	(0.209)
Observations	18,790	10,793	1,182	746

Note: Mean of each variable with standard deviation in parentheses.

This table gives summary statistics of variables used in analyzing sample of drivers who was conducted a vehicle search in column 1; a driver search in column 2; a passenger search in column 3; searched by police dog in column 4. Only cases in which police officers did not find drug, contraband, alcohol, or illegal property are examined.

Table 4.11 Police officer discretionary decisions on length of stops for samples of drivers with whom police officers conduct a vehilce, driver, passenger, or police dog search

(a) Driver characteristics

	Vehicle	Driver	Passenger	Police dog
Age 16-21	-1.015***	-0.792	1.351	-4.572***
	(0.352)	(0.527)	(1.486)	(1.368)
Age 22-30	-0.012	-0.039	0.576	-2.415**
	(0.285)	(0.421)	(1.668)	(1.190)
Age 51-64	-0.685*	-1.257	0.991	-2.844
	(0.378)	(0.812)	(2.979)	(1.826)
Age >= 65	-1.949***	-1.951	-0.205	-4.448**
	(0.643)	(1.578)	(4.136)	(1.906)
Female driver	-0.076	0.228	-1.193	-1.700
	(0.258)	(0.465)	(1.430)	(1.243)
Black driver	1.653***	-1.340**	7.924***	1.458
	(0.426)	(0.661)	(3.058)	(1.553)
Asian driver	3.325**	2.008	-5.929**	-2.971
	(1.372)	(2.517)	(2.741)	(2.440)
Hispanic driver	3.464***	-1.047**	2.659	4.130*
	(0.505)	(0.482)	(2.014)	(2.184)
Observations	18,790	10,793	1,182	746

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Other characteristics

	Vehicle	Driver	Passenger	Police dog
Night	1.215***	1.380**	1.755	1.734
	(0.277)	(0.540)	(1.247)	(1.610)
End of month	-0.456**	0.587	-0.164	-0.614
	(0.227)	(0.374)	(1.467)	(1.339)
Black * Night	-0.654	-0.265	-3.967*	-1.059
	(0.542)	(0.788)	(2.205)	(2.429)
Equipment violation	-1.425***	-1.101**	-2.639**	1.447
	(0.294)	(0.451)	(1.273)	(1.142)
License/Registration	1.210***	-0.420	0.185	3.804*
	(0.356)	(0.569)	(2.363)	(2.217)
Commercial Vehicle	16.091***	5.794	15.916**	12.472***
	(2.052)	(3.796)	(6.794)	(3.610)
Observations	18,790	10,793	1,182	746

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows results of regressing duration of stop on variables (shown in table) and controlling for analyzing month in which traffic stop was made with police agency fixed-effects and cluster over location zip code where the driver was stopped for sample of drivers who was conducted a vehicle search in column 1; a driver search in column 2; a passenger search in column 3; searched by police dog in column 4. Only cases in which police officers did not find drug, contraband, alcohol, or illegal property are examined.

Table 4.12 Summary statistics of variables for samples of drivers that police officers conduct a vehicle, driver, passenger or police dog search

	Vehicle	Driver	Passenger	Police dog
Duration of stop	21.98	23.78	23.66	27.20
	(19.93)	(20.94)	(18.68)	(20.92)
Age 16-21	0.187	0.170	0.289	0.199
	(0.390)	(0.376)	(0.453)	(0.399)
Age 22-30	0.374	0.392	0.400	0.354
	(0.484)	(0.488)	(0.490)	(0.478)
Age 51-64	0.0734	0.0624	0.0422	0.0795
	(0.261)	(0.242)	(0.201)	(0.270)
Age >= 65	0.0133	0.00706	0.00608	0.0154
	(0.115)	(0.0837)	(0.0777)	(0.123)
Female driver	0.248	0.209	0.235	0.193
	(0.432)	(0.407)	(0.424)	(0.394)
Black driver	0.301	0.339	0.411	0.310
	(0.459)	(0.473)	(0.492)	(0.463)
Asian driver	0.00987	0.00936	0.00630	0.0121
	(0.0989)	(0.0963)	(0.0791)	(0.109)
Hispanic driver	0.225	0.282	0.192	0.153
	(0.418)	(0.450)	(0.394)	(0.360)
Stopped at night	0.591	0.598	0.644	0.549
	(0.492)	(0.490)	(0.479)	(0.498)
End of month	0.269	0.270	0.268	0.270
	(0.444)	(0.444)	(0.443)	(0.444)
Black * Night	0.175	0.198	0.264	0.178
	(0.380)	(0.399)	(0.441)	(0.383)
Equipment violation	0.227	0.226	0.290	0.246
	(0.419)	(0.418)	(0.454)	(0.431)
License/Registration	0.148	0.158	0.139	0.0874
	(0.355)	(0.365)	(0.346)	(0.282)
Commercial Vehicle	0.00347	0.00180	0.000890	0.0395
	(0.0588)	(0.0424)	(0.0298)	(0.195)
Observations	62,195	54,368	13,485	2,404

Note: Mean of each variable with standard deviation in parentheses.

This table gives summary statistics of variables used in analyzing sample of drivers who was conducted a vehicle search in column 1; a driver search in column 2; a passenger search in column 3; searched by police dog in column 4. Only cases in which police officers did not find drug, contraband, alcohol, or illegal property are examined. Cases that police officers conduct several searches at one time are included.

Table 4.13 Police officer discretionary decisions on length of stops for samples of drivers with whom police officers conduct a vehilce, driver, passenger, or police dog search

(a) Driver characteristics

	Vehicle	Driver	Passenger	Police dog
Age 16-21	-1.689***	-1.473***	-1.186***	-3.323***
	(0.226)	(0.240)	(0.386)	(1.082)
Age 22-30	-0.475***	-0.406**	-0.706*	-1.818*
	(0.170)	(0.180)	(0.367)	(1.005)
Age 51-64	-0.192	0.259	0.466	-1.496
	(0.318)	(0.386)	(0.811)	(1.916)
Age >= 65	-1.905***	-1.024	-2.421*	-4.267
	(0.568)	(0.826)	(1.338)	(2.884)
Female driver	0.358*	0.655***	0.052	0.423
	(0.188)	(0.214)	(0.382)	(1.079)
Black driver	0.992***	0.127	1.541***	1.969
	(0.269)	(0.286)	(0.560)	(1.355)
Asian driver	1.631*	1.065	1.881	-0.521
	(0.975)	(0.903)	(2.997)	(6.441)
Hispanic driver	1.351***	0.230	1.290***	8.141***
	(0.245)	(0.215)	(0.468)	(1.981)
Observations	62,195	54,368	13,485	2,404

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Other characteristics

	Vehicle	Driver	Passenger	Police dog
Night	1.105***	1.059***	1.394***	2.029*
	(0.209)	(0.235)	(0.450)	(1.094)
End of month	-0.053	0.334*	1.086***	-2.173**
	(0.159)	(0.181)	(0.389)	(0.983)
Black * Night	-1.139***	-1.138***	-1.671***	-1.012
	(0.305)	(0.342)	(0.613)	(1.725)
Equipment violation	-0.924***	-0.777***	-1.255***	1.030
	(0.205)	(0.204)	(0.333)	(0.934)
License/Registration	0.017	-0.487**	-0.343	0.907
	(0.215)	(0.217)	(0.457)	(1.362)
Commercial Vehicle	17.248***	16.506***	20.850***	17.014***
	(2.476)	(3.721)	(6.938)	(4.528)
Observations	62,195	54,368	13,485	2,404

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows results of regressing duration of stop on variables (shown in table) and controlling for analyzing month in which traffic stop was made with police agency fixed-effects and cluster over location zip code where the driver was stopped for sample of drivers who was conducted a vehicle search in column 1; a driver search in column 2; a passenger search in column 3; searched by police dog in column 4. Only cases in which police officers did not find drug, contraband, alcohol, or illegal property are examined. Cases that police officers conduct several searches at one time are included.

Table 4.14 Summary statistics of variables for samples of drivers who were searched, searched and nothing found, searched and found

	Search conducted	Nothing found	Found
Duration of stop	23.94	22.11	30.23
	(22.02)	(20.03)	(26.86)
Age 16-21 years old	0.207	0.182	0.291
	(0.405)	(0.386)	(0.454)
Age 22-30 years old	0.379	0.375	0.392
	(0.485)	(0.484)	(0.488)
Age 51-64 years old	0.0665	0.0726	0.0453
	(0.249)	(0.260)	(0.208)
Age >= 65 years old	0.0111	0.0127	0.00572
	(0.105)	(0.112)	(0.0754)
Female driver	0.236	0.247	0.199
	(0.425)	(0.431)	(0.399)
Black driver	0.304	0.303	0.308
	(0.460)	(0.459)	(0.462)
Asian driver	0.00936	0.00997	0.00729
	(0.0963)	(0.0993)	(0.0851)
Hispanic driver	0.210	0.234	0.127
	(0.407)	(0.423)	(0.333)
Stopped at night	0.608	0.585	0.688
	(0.488)	(0.493)	(0.463)
End of month	0.271	0.270	0.276
	(0.445)	(0.444)	(0.447)
Black driver * Night	0.183	0.176	0.208
	(0.387)	(0.380)	(0.406)
Equipment violation	0.231	0.226	0.246
	(0.421)	(0.418)	(0.431)
License/Registration	0.139	0.150	0.102
	(0.346)	(0.357)	(0.303)
Commercial Vehicle	0.00311	0.00369	0.00111
	(0.0557)	(0.0606)	(0.0333)
Observations	96,222	74,542	21,680

Note: Mean of each variable with standard deviation in parentheses.

This table gives summary statistics of variables used in analyzing sample of drivers who was conducted a vehicle search in column 1; search conducted and nothing found in column 2; search conducted and found illegal property in column 3.

Table 4.15 Police officer discretionary decisions on length of stops for samples of drivers who were searched, searched and not found, searched and found

(a) Driver characteristics

	Search conducted	Nothing found	Found
Age 16-21	-0.656***	-1.563***	-0.905**
	(0.193)	(0.209)	(0.443)
Age 22-30	-0.319**	-0.362**	-1.278***
	(0.149)	(0.160)	(0.394)
Age 51-64	-0.512*	-0.273	0.328
	(0.281)	(0.294)	(0.809)
Age >= 65	-2.302***	-1.993***	-0.600
	(0.531)	(0.544)	(1.848)
Female driver	0.032	0.236	0.880**
	(0.161)	(0.171)	(0.403)
Black driver	0.642**	1.141***	-0.334
	(0.254)	(0.254)	(0.581)
Asian driver	1.561*	1.533*	3.970*
	(0.867)	(0.903)	(2.206)
Hispanic driver	0.391*	1.271***	-0.293
	(0.217)	(0.223)	(0.558)
Observations	96,222	74,542	21,680

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Other characteristics

	Search conducted	Nothing found	Found
Night	1.839***	1.426***	1.641***
	(0.208)	(0.201)	(0.460)
End of month	-0.034	0.045	-0.229
	(0.140)	(0.153)	(0.342)
Black * Night	-1.367***	-1.386***	-0.525
	(0.279)	(0.290)	(0.638)
Equipment violation	-0.943***	-1.004***	-0.749**
	(0.175)	(0.191)	(0.374)
License/Registration	-0.205	0.084	-0.133
	(0.195)	(0.198)	(0.461)
Commercial Vehicle	13.946***	14.756***	7.762
	(1.867)	(2.067)	(5.685)
Observations	96,222	74,542	21,680

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows results of regressing duration of stop on variables (shown in table) and controlling for analyzing month in which traffic stop was made with police agency fixed-effects and cluster over location zip code where the driver was stopped for sample of drivers who was conducted a vehicle search in column 1; search conducted and nothing found in column 2; search conducted and found illegal property in column 3.

Table 4.16 Covariate balance before and after propensity score matching

	Original sample				Kernel matching sample			
	White	Black	Bias %	p-value	White	Black	Bias %	p-value
Female	0.404	0.363	8.4	0.001	0.404	0.397	1.5	0.539
Age 16-21	0.124	0.158	-9.7	<0.001	0.124	0.121	0.8	0.726
Age 22-30	0.314	0.363	-10.5	<0.001	0.314	0.329	-3.1	0.177
Age 51-64	0.139	0.107	9.8	<0.001	0.139	0.125	4.3	0.076
Age >= 65	0.045	0.025	11.1	<0.001	0.045	0.039	3.1	0.236
Equipment	0.245	0.280	-7.9	0.002	0.245	0.250	-1.00	0.664
License	0.112	0.130	-5.3	0.036	0.112	0.114	-0.4	0.855
Moving	0.636	0.588	10	<0.001	0.636	0.632	0.9	0.686
Night	0.463	0.521	-11.7	<0.001	0.463	0.475	-2.3	0.318
Observation	3,619	2,648			3,619	2,648		
	White	Hispanic	Bias %	p-value	White	Hispanic	Bias %	p-value
Female	0.404	0.288	24.5	<0.001	0.404	0.409	-1.1	0.655
Age 16-21	0.124	0.202	-21.3	<0.001	0.124	0.115	2.3	0.262
Age 22-30	0.314	0.347	-7.0	<0.001	0.314	0.333	-4.2	0.072
Age 51-64	0.139	0.067	23.8	<0.001	0.139	0.117	7.2	0.005
Age >= 65	0.045	0.139	18.4	<0.001	0.045	0.048	-2.1	0.481
Equipment	0.245	0.274	-6.6	0.001	0.245	0.258	-2.9	0.217
License	0.112	0.094	5.9	0.001	0.112	0.094	6.2	0.009
Moving	0.636	0.626	2.1	0.266	0.636	0.644	-1.6	0.494
Night	0.463	0.471	-1.5	0.417	0.463	0.464	-0.2	0.934
Observation	3,619	11,927			3,619	11,927		
	White	Asian	Bias %	p-value	White	Asian	Bias %	p-value
Female	0.404	0.351	11.0	0.253	0.404	0.359	9.4	<0.001
Age 16-21	0.124	0.149	-7.3	0.426	0.124	0.148	-6.9	0.003
Age 22-30	0.314	0.307	1.5	0.876	0.314	0.305	1.9	0.413
Age 51-64	0.139	0.105	10.2	0.308	0.139	0.104	10.7	<0.001
Age >= 65	0.045	0.035	4.9	0.622	0.045	0.036	4.3	0.066
Equipment	0.245	0.158	21.8	0.032	0.245	0.159	21.7	<0.001
License	0.112	0.061	18.2	0.087	0.112	0.061	18.2	<0.001
Moving	0.636	0.763	-27.9	0.005	0.636	0.772	-29.9	<0.001
Night	0.463	0.447	3.1	0.744	0.463	0.450	2.6	0.274
Observation	3,619	114			3,619	114		

This table gives descriptive statistics of balancing property of covariates used in analysis racial disparity on police officer decisions

Table 4.17 The racial disparity in police officer decisions

	Original sample				Kernal matching sample			
	White	Black	Diff	T-test	White	Black	Diff	T-test
Ticketed	0.398	0.395	0.003	0.23	0.398	0.402	-0.0039	-0.31
Searched	0.064	0.146	-0.082	-10.9	0.064	0.134	-0.070	-8.64
Duration	10.856	12.162	-1.307	-6.14	10.856	12.002	-1.146	-5.15
Duration <10	0.409	0.332	0.078	6.29	0.409	0.342	0.068	5.43
	White	Hispanic	Diff	T-test	White	Hispanic	Diff	T-test
Ticketed	0.398	0,446	-0.049	-5.17	0.398	0.434	-0.036	-3.74
Searched	0.064	0.164	-0.101	-15.39	0.064	0.141	-0.078	-13.71
Duration	10.856	12.385	-1.529	-9.34	10.856	12.106	-1.25	-7.86
Duration <10	0.409	0.334	0.075	8.25	0.409	0.357	0.052	5.46
	White	Asian	Diff	T-test	White	Asian	Diff	T-test
Ticketed	0.398	0.421	-0.023	-0.50	0.398	0.426	-0.029	-0.60
Searched	0.064	0.044	0.020	0.85	0.064	0.045	0.019	0.95
Duration	10.856	11.771	-0.916	-1.23	10.856	11.548	-0.692	-0.59
Duration <10	0.409	0.429	-0.021	-0.44	0.409	0.434	-0.025	-0.53

This table gives the difference in search rate, ticket rate, and duration of stop across races.

CHAPTER 5
Conclusion

This dissertation examine the effect of factors that influence police officer discretionary decisions. The decisions include stopping and searching, ticketing, fine amounts and duration of stops. We analyze the decisions by using various econometrics methods: the outcome test, fixed-effects model, quantile fixed-effects model, Heckman selection model and propensity score matching method. We find that characteristics of both drivers and police officers have significantly influenced on officer decisions.

In the first study, we show that police officers are more likely to issue lower fine to in-town, in-state, female, black, old drivers than out-of-town, out-of-state, male, middle-aged drivers, respectively. We also find that police officers are more lenient with drivers who own a commercial drivers license. For speeding violations, police officers will be stricter with drivers speeding in high-speed zones, in terms of both probability of receiving a ticket and fine amount. These factors influence police officers differently across quantiles. In addition, we show that if a police officer issue a ticket in an encounter, he/she will be more lenient with the next pulled-over driver. We also find that "ticket quota" does not exist.

In the second study, we confirm that driver characteristics influence police officer discretionary decisions. We also show that police officer characteristics influence their decisions as well. Particularly, female and highly-experienced police officers issue higher fine amount than male and less-experienced police officers, respectively. White police officers are more lenient than police officers of other races while Asian officers are the strictest. We also show that white drivers are treated the most lenient regardless of police officer race. White police officers are strictest toward Asian drivers while black and Asian police officers are strictest toward Hispanic drivers.

In the third study, although more white drivers are stopped and searched than drivers of other races, white drivers are treated with the most leniency in terms of probability of receiving a ticket and duration of stops. Comparing the success rate of finding contraband, we find that police officers are less likely to find contraband from female and old drivers, which suggests that police officers are stricter to them than male and middle-aged drivers. By using either police agency fixed effects model or propensity score matching method, we find that police officers are less likely to issue female and old drivers a ticket and stop them for fewer time than male and middle-aged drivers.

This study has contributed to the existing literature in three ways. First, this is the first study to quantify police officer discretion. Second, it is also the first to look at duration of stops in minutes to examine what influences police officer behavior. Third, by using various econometric methods, this study gives a detailed analysis of factors that influence police officer discretionary decisions.

This study have implications for police department policy. The study urges that police departments develop policies to prohibit the use of personal characteristics to make the decisions. Police training in work ethics, department policies are needed to educate police officers about the outcomes and consequence of their decisions. In addition, the study suggests that there should be guidelines for the limit of police officer discretion in order to prevent the false uses of discretion. Lastly, the study contributes to the literature of research on police officer decisions which assists the judges on the claims of law enforcement.

However, there are some data limitations. First, in both data, we do not know the driving record and criminal record of driver. When police officer decide the levels of fine, they also take that information into consideration. Second, we only two month data of Massachusetts traffic citations. The conclusion regarding "ticket quota" may therefore be incorrect. Third, in Illinois data, we do not have data on police officer characteristics and several other driver characteristics such as resident status and criminal record. Those characteristics may have significant effects on police officer decisions as well. Lastly, police officers who write the citations/ traffic stop sheet in these two data sets are informed about the usage of data in advance. Some police officers therefore may change their usual stopping/ticketing decisions in order to comply the policies. Ideally, future research can conduct a randomized experiment in which police officers are not notified about the purposes of collecting data.

Given that decision-making by police officers and how they apply discretion is complicated, more studies on police officer discretion are needed in order to alert police officers to the situation. In addition, a countrywide study is recommended to identify the precise effect of factor influencing police officer decisions since the effects may differ in each state.

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