Detecting Racial Bias in Speed Discounting: Evidence from Speeding Tickets in Boston

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Abstract

In this paper, we focus on a particular kind of discretionary behavior on the part of traffic officers when issuing speeding tickets–what we term *speed discounting*. It is anecdotally said that officers often give motorists a break by reporting a lower speed on their citation than the actual speed that they observe the vehicle doing. Verifying the level of police discretion in the speed discounting behavior and ascertaining the presence of racial bias among police officers are the main objectives of this paper. Using data on speeding tickets in Boston, we find that, compared to white officers, minority officers are harsher to all motorists, but especially to minority ones. This result appears to be stronger in situations involving Hispanic officers, infrequently-ticketing officers, male motorists, those driving old vehicles, and minority neighborhoods.

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> Although [the officer] wrote the man a ticket for only 10 m.p.h. over the 35 m.p.h. limit, he made a note in the top right-hand corner of the ticket: "64." Through a Boston police spokeswoman, [he] said that notation meant the driver was actually going 64 m.p.h., or 29 m.p.h. over the limit. The spokeswoman said [the officer] would sometimes lower the speed on a ticket, to save a driver a high fine. But the notation was there in case the driver challenged the ticket in court (Bill Dedman and Francie Latour, *The Boston Globe*, July 20, 2003).

1 INTRODUCTION

Police officers are allowed to exercise a significant amount of street-level discretion. A crucial issue is to ascertain whether or not they use their bestowed power appropriately (e.g. overlooking mildly-speeding vehicles to facilitate the traffic flow). When an officer enforces traffic laws strictly, when observing a speeding vehicle, he or she will stop it, give a ticket to the motorist reporting its actual speed when it was stopped, and impose a fine according to the statutory formula. An officer using discretion, on the other hand, could 1) not even stop the vehicle, 2) stop it but just let it go with an oral warning, 3) stop it and give a written warning, or 4) stop it and issue a ticket but discount the speed and/or the fine.[1] Various factors, such as the driver's age, gender, race, attitude, and financial situation, apparently play significant roles in officers' decisions.[2]

In this paper, we focus on a particular type of discretionary behavior: what we term *speed discounting*; it is anecdotally said that officers often give a "break" to motorists by reporting a lower speed than their actual speed (as the quote in the beginning of the paper indicates). Verifying the level of the police discretion in the speed discounting behavior and the presence of a racial bias among officers are crucial points that we will focus on in this paper.

Figure 1 is an important starting point to illustrate the presence of speed discounting.[3] The graph is a histogram of the reported speeds on 25,738 speeding tickets issued by Boston

[1] There are also other, subtle things that officers can control, such as the length of stopping time, language, and friendliness, which can affect the disutility of the motorist.

[2] "There are always mitigating circumstances in a stop," an officer said in an interview with the Boston Globe. "Anything could be said or could happen. Attitudes, people talking back to you. The circumstances change with each individual driver." The officer also admitted that he rarely gave fines to elderly drivers, "presuming they were on a fixed income" (Dedman and Latour, 2003).

[3] In Appendix Figure 1, we present the distribution of speed for each race of drivers. They are very similar.

police officers between April 2002 and November 2003. The most outstanding feature is that more than 30% of tickets are cited for driving at exactly 10 m.p.h. over the limit (hereafter, unless otherwise noted, the speed is always denoted as the miles per hour above the limit). There also exist other less outstanding spikes at some specific speed levels, such as 15 and 20. The graph indicates that the speeds reported on tickets – especially at the spikes – are unlikely to be the actual speeds.[4] Rather, the histogram reveals that officers' discretionary speed reporting distorts the distribution, especially in the range of 10–14. As we will elaborate later, conditional on getting ticketed at speed levels of 10 or slightly higher, the fact that a motorist gets cited for driving at exactly 10 most likely indicates that the officer gives speed discounting to the motorist. Our identification strategy is to exploit the unique spike at speed 10 to elicit officers' discretionary behavior and to test for the presence of racial bias in that particular behavior.

To test for racial bias, we employ two empirical approaches, both of which are well recognized in the racial profiling literature. First, in the spirit of Anwar and Fang (2006), we set up a model in which unbiased officers care about the likelihood of recidivism when drivers are leniently treated. Biased officers have different costs of treating drivers harshly depending on their race. Based on this model, we can apply the rank-order test with the null of no relative racial bias. Second, following Price and Wolfers (2007) and Antonovics and Knight (2009), we employ the difference-in-difference (DD) approach. The idea is that, as long as the motorists in the sample are similar in terms of the underlying offenses after controlling for a rich set of control variables, variation in the likelihood of receiving speed discounting across pairs of driver race and officer race will be suggestive of racial bias among officers. As we will elaborate, this approach is likely to be valid in our application. Despite its theoretical weakness, the advantage of the DD approach is that we can examine alternative outcomes such as the amount of speeding fines and total number of tickets. Also we can estimate a joint decision model of speed discounting and ticketing. The two empirical approaches are based on different assumptions, so reaching the same result will increase confidence in our findings.[5]

[4]Clarke (1996), using about 16.5 million observations in Illinois, found that the speed distribution – recorded mechanically, not by officers – is normally distributed and centered at the speed limit under free flow conditions.

[5]The DD approach is valid under certain conditions (Fang and Persico, 2009; Persico, 2009; Rowe, 2009). We will discuss the validity conditions in our context later. The rank-order test is also restrictive in the sense that it is based on a particular model of officers' strategy conditional on stopping and ticketing.

Indeed, we consistently find evidence of officers' racial bias from both approaches. The rank-order test rejects the null of no racial bias. We find that minority officers are not less biased against minority drivers than white officers. In particular, Hispanic officers are harsher to minority motorists, though they are as lenient to white motorists as white officers. From the DD method, we also find that, compared to white officers, minority officers are harsher on minority motorists. The result is robust to controlling for motorists' zip codes, as well as to controlling for different types of neighborhoods where citations were issued and to correcting for the potential selection bias associated with officers' ticketing behavior.

Hispanic officers are as lenient to white drivers as white officers who are lenient to all drivers. Even when we focus on African-American and Hispanic officers only, we find that at least one racial group is biased. Compared to white and Hispanic officers, African-American officers are stricter to all drivers, but in particular they are also harsher to minority drivers. We also find that our results appear stronger in situations involving infrequently ticketing officers, male motorists, motorists driving old vehicles, and those driving in minority residential neighborhoods.

Obviously, speed discounting is just one dimension of the police discretion. To avoid the fallacy of slanting, we examine other types of disparate treatment on the part of officers in issuing speeding tickets, apart from speed discounting. We find that minority officers are more likely to issue tickets than warnings to minority motorists. Similarly, we find that minority officers issue more tickets *per day* to minority motorists than they issue to white motorists. On the other hand, there is no evidence of any disparate treatment between the two genders, and little evidence regarding disparate treatment of individuals of different ages. Lastly, we find no evidence of minority-on-minority disparity in terms of "fine" discounting.

The finding that minority officers treat minority motorists relatively more harshly is somewhat unexpected, since officers' racial biases would typically imply that white officers treat minority motorists more strictly, or vice versa. We realize that it is important to know the status of minority officers within the police force and perceptions regarding them in the communities they serve, and knowing more details of interactions between officers and motorists during vehicle stops would be invaluable. One lesson from this paper is that officers could be involved in racially-biased behavior in many different forms for various internal and external reasons.

The paper is organized as follows. Section 2 discusses the related literature. In Section 3 we argue that the clustering of tickets at the speed of 10 results from officers' speed discounting behavior. Section 4 explains our identification strategy. We discuss the conditions under which the indicator of getting cited at exactly 10 is a valid proxy variable for the officer's discretion. We also modify Anwar and Fang's model to apply the rank-order test in our context. Lastly, we support the validity of the DD estimation method. Section 5 presents empirical results. We also perform various robustness checks. In Section 6, we explore some probable causes for our puzzling findings. Section 7 concludes.

2 RELATED LITERATURE

It is worth discussing, at the outset, how this paper and its research topic are related to the recently growing body of literature on racial profiling in vehicle searches (Knowles, Persico, and Todd, 2001; Anwar and Fang, 2006; Antonovics and Knight, 2009). The main point here is that officers' ticketing and vehicle-searching behaviors are *different* in nature. First, in the case of speeding violation, officers can–albeit with some error–directly observe the degree of the offense, i.e. the speed over the limit. Thus, officers' subsequent decisions only relate to how strictly they should handle the case. On the other hand, officers decide whether to conduct vehicle searches without having observed the presence and degree of any illegal behavior. Thus, officers necessarily infer the probability of an offense by processing all available information before making a decision as to how to proceed. This mind process is unobservable even to the motorist, so it is difficult for any third party to figure out whether or not the officer utilized the driver's race as a productive resource.[6]

One may think that officers also make statistical inferences in the case of speeding violations. For example, officers would be expected to treat certain motorists more strictly if these motorists seem to tend to break the law again in the future when treated leniently. We will consider this in Section 3 when we modify Anwar and Fang's model. However, intuitively, it

[6]The identification approaches in the literature are various, and the results are mixed. Knowles, Persico and Todd (2001) show that racially biased monitoring implies that the equilibrium rate at which contraband is seized (the "hit rate") is lower for the groups subject to bias. In some data sets, the race of the officers is also observable, which makes different approaches feasible. Antonovics and Knight (2009) use the same Boston data that we use in this paper, and test whether officers are more likely to conduct a search if the race of the officer differs from that of the driver. Anwar and Fang (2006) propose the rank-order test for relative racial prejudice. Using the Florida highway data, they cannot reject the null hypothesis of no racial bias, which, however, as they warn readers in their paper, does not mean that racial bias does not exist. Close and Mason (2007) develop a pairwise-comparison outcome test and, using the same Florida data, reject the null hypothesis of no discrimination. Persico (2009) provides a general framework that can be adapted to various identification strategies.

seems unlikely that race is informative of such recidivism, particularly for moderate speeders like the ones we are focusing on in this paper. It is also hard to believe that the degree of an officer's strictness in issuing speeding tickets will be sufficient to alter a motorist's speeding behavior in the future, since driving style has been found to be habitual to a certain extent (Lawpoolsri et al., 2007).

Second, in vehicle searches officers deal with those people who are potentially major offenders and felons. Thus, it may make sense, at least theoretically, for officers to target a particular segment of the population. On the other hand, speeding motorists are likely to be "non-criminal" people (in fact, a strong case could be made that criminals would not rationally speed). Similarly, while most officers might consider vehicle searching a high-risk task, issuing speeding tickets is likely to be considered mundane or routine.

Lastly, officers who are lenient in vehicle searches could be accused of abandoning their duty, while leniency in issuing speeding tickets could even be considered "humane" in cases involving first-time offenders and drivers with seemingly limited financial means. In short, it would not be surprising to find that officers behave differently in these two very different cases. However, it is still interesting to compare our findings with those in the vehicle search literature.

While there has been no work on speed discounting or racial disparities in the speed discounting context to date, a related strand of research is concerned with officers' decision-making regarding how they stop vehicles, and whether they issue tickets or warnings to drivers with certain characteristics. Most papers in this strand attempt to test for racial bias of officers. The state-sponsored Northeastern Study (Farrell et al., 2004) uses the Massachusetts data our Boston sample comes from. Their results reveal that there are major disparities in the ticketing behavior of officers toward motorists of different races and genders.[7] The study employs the standard "benchmark test," which compares the shares of racial minorities in the population to their shares in the sample of drivers ticketed.[8] There is no mention of the speed-discounting phenomenon in this extensive study.

There have been attempts to overcome the benchmark test. McConnell and Scheidegger

[7]This naturally raises a red flag regarding the officers' intentions, given that a study by Lamberth (1996), which examined the driving habits of African-American and white motorists on Maryland highways, found no difference in the rates at which these two segments of motorists engaged in speeding.

[8]The racial composition of the Census-based residential population represents the racial composition of drivers on the road poorly. For a criticism of the residential population benchmark approach, refer to Riley and Ridgeway (2004) and, more generally, Engel and Calnon (2004).

(2001) compare speeding tickets issued by air-patrol officers and by ground-patrol officers. The assumption is that the race of the driver cannot possibly be determined by any air-patrol officer, while that is not the case for a ground-patrol officer. Ridgeway (2006) uses the propensity score matching method to construct comparable groups. Grogger and Ridgeway (2006) compare the race distribution of drivers stopped during daylight with the counterpart distribution of those stopped at night. The results from these studies show that apparent racial disparities in both stopping and ticketing rates do not necessarily reflect officers' racial biases.

Some papers have looked at issues other than racial disparities in officers' behaviors. Blalock, DeVaro, Leventhal, and Simon (2007) examine traffic ticketing data from Bloomington and Highland Park in Illinois, Wichita, Boston, and the entire state of Tennessee, and find that women are more likely to receive citations in three of the five locations, while men are more likely to receive citations in the other two locations. Rowe (2009) extends Anwar and Fang's rank test to examine gender bias in ticketing. Makowsky and Stratmann (2009), using the Massachusetts traffic data, examine whether local police officers pursue certain objectives other than effective policing, such as raising local government revenues from out-of-towners. They examine not only officers' ticketing behavior, but also how they impose speeding fines. Since speed discounting is one kind of officers' discretionary behavior, in order to get a complete picture, we will also examine ticketing and fine discounting.

3 DATA

3.1 Sample and Descriptive Statistics

The original raw data contain 2,001,562 traffic citations issued in Massachusetts between April 2001 and November 2002. The data were collected beginning April 1, 2001; the collection of the data was enabled by the Massachusetts legislature's passing "An Act Providing for the Collection of the Data Relative to Traffic Stops" in August 2000. The data include information on the Massachusetts Uniform Citation about the motorists' race, gender, age, and home town, as well as when they were cited and where the vehicles were stopped, and so on. All information obtained was based upon officers' reporting (Farrell et al., 2004).

We merged the citation-level data with the officer personnel data obtained from the Boston police department. The administrative personnel data include officers' race, gender, and experience in the force. In the merged data, there are only local police officers (i.e. no state police officers), with 161,133 matched citations issued by Boston police officers within Boston between April 2001 and November 2002.[9] Within that merged data set, we focus on speeding tickets and warnings, which account for 26% of all citations, the largest single category (warning records were computerized in the first two months only, i.e. in April and May, 2001). We had to delete observations with missing information. First, we deleted 2,041 citations without the vehicle speed and 3,128 citations without the motorists' races.[10] We also deleted 1,875 citations in which drivers are not categorized as white, African-American or Hispanic, and 1,031 additional citations issued by Asian officers. Finally, for reasons explained below, we will focus on a narrow speed range between 10 and 14. Consequently, our sample includes 14,253 speeding tickets and 1,984 warnings.

Table 1 provides the descriptive statistics. In Column 1, for all tickets between 10 and 14, there are several notable facts:

- The motorists who received speeding tickets were rather young. The average age is 36. And about 65% of cited drivers are male.

- Almost all cited motorists are Massachusetts residents, while about 50% of them were stopped and given citations in their own neighborhood.

- African-American drivers account for 32% of speeding tickets, and Hispanics for 12%. According to the 2007 American Community Survey, non-Hispanic blacks account for 22.2% of the Boston population, and Hispanics for 15.6%. If driving habits do not differ by drivers' races – as is indicated by Knowles, Persico, and Todd (2001) and Lamberth (1996), and especially if the racial composition of the Census-based residential population appropriately represents the racial composition of drivers on the road, this may indicate that African-American motorists get slightly more speeding tickets per capita.

[9] In the literature, there is a concern about using data on vehicle stops and searches on local streets, because officers could obtain additional information about drivers from people in the neighborhood, and the amount of information might depend on the officers' race (Anwar and Fang, 2006). However, this is unlikely to happen when issuing speeding tickets.

[10] The motorist's race is determined by the officer's reporting, and in some cases officers may not be able to determine drivers' races unambiguously. This might explain a portion of the citations with a missing driver race. By the same token, it is also possible that the recorded race is different from the actual one. This should not be a problem simply because, for the purpose of this paper, it is officers' perceptions about the drivers' races that are relevant.

- About 32% of speeding tickets are issued by African-American officers, while 10% are issued by Hispanic officers. In our restricted sample, 24% of officers are African-Americans and 10% are Hispanic. This means that African-American officers issue more speeding tickets per capita.
- When the racial composition of officers is compared to that of the population, Hispanics are significantly underrepresented in the police, while African-Americans are fairly well represented.
- About 97% of speeding tickets are issued by male officers, who constitute 87% of the police force. According to the 2000 Law Enforcement Management and Administrative Statistics (LEMAS), among all full-time sworn officers of all races in Boston, 24% of officers are African-American, and only about 6% are Hispanic.
- A majority of speeding tickets (62%) were issued in a 30 mile speed zone.
- Finally, and perhaps most importantly, 57% of speeding tickets were issued exactly at 10 miles per hour above the posted speed limit.

3.2 Massive Clustering of Tickets at 10 above

The most distinctive feature of the data is the clustering of tickets at 10. Before arguing that officers' speed discounting accounts for this massive clustering, we will exclude the possibility that the drivers' behavior could explain the heaping of tickets at that very specific speed. According to the Massachusetts statutory formula, for the first ten miles above the speed limit, the fine is $75, and then it rises by ten dollars for each additional mile. Given that the fine amount is constant up to the speed of 10, it may surely be optimal for some motorists with certain preferences to maintain that speed. It is, however, difficult to believe that so many motorists could control their vehicle speed so delicately and strategically, particularly considering traffic conditions in Boston.[11] In particular, the decision whether to drive at 10 or 11 cannot possibly be an accurately-intended choice by motorists.

[11] Appendix Figure 2 shows the distribution of reported speeds for speeding tickets issued in the City of Bloomington between 2004 and 2007. There is no notable spike. There, fines are $75 up to 20 m.p.h. above the limit, then increase to $95 for up to 30 (and in addition, some driving points will be accumulated, according to the Illinois point system; 5 points up to 10, 15 points up to 14, and so on). Due to the constant fine over a wider range (1-20), there is a weaker incentive for officers to give speed discounting. It seems likely that officers are rarely lenient to motorists who exceed the speed limit by more than 20 m.p.h. The Bloomington data alone indicate that the unusual speed distribution in Boston does not result from drivers' behavior at all.

Suppose for a moment that motorists can choose their vehicle speed precisely. In that case, if the optimal speed were determined by a benefit function that is differentiable and continuous in motorists' characteristics, those characteristics should not have discretely jumped between 10 and nearby speeds. This is a testable hypothesis. In Table 1, we compare various characteristics of motorists cited at 10 with motorists cited at 11 and with those cited at a speed level between 11 and 14. Contrary to the hypothesis, we find that most motorist variables significantly change by a small change in speed. Motorists who are ticketed at 10 are older, more likely to be from out of town, more likely to be male, and less likely to be African-American or Hispanic.

Likewise, if the spike at 10 were totally explained by motorists' driving behavior, then officers' characteristics should not change discretely between 10 and the nearby speeds. Again we find that the racial composition of officers differs remarkably at very similar speeds. Among officers who issued speeding tickets at 10, 18% and 12% are African-American and Hispanic, respectively. On the other hand, of those who issued tickets between 11 and 14, 51% and 8% are African-American and Hispanic. Similar differences are found between 10 and 11. Officers who issued tickets at 10 are predominantly white, while a majority of those who issued tickets at a nearby speed are African-American.

The above findings suggest that the spike at 10 is to a degree a consequence of officers' discretionary behavior. As the quote at the beginning of the paper indicates, there exists strong anecdotal evidence of officers' speed discounting that lends real-life support to our diagnosis. The remaining question is why officers discount the speed to those particular round numbers, especially 10. To answer the question, first, consider a police officer who gains some utility from citing motorists at a speed closer to the actual speed, but, at the same time, cares about the fines they will pay. Recall that whether the officer issues tickets at 10 or less does not matter at all in terms of the fines the motorists will pay. Thus, for those drivers who actually drove at a speed higher than 10 but received speed discounting, 10 would be the most natural level of speed that such officers would choose to report.

Second, once officers decide to give a break to some drivers, some prominent speed levels may well emerge as cognitive reference points. It is a general tendency of people to prefer round numbers like 10 and 15 (Johnson et al., 2007). Once using such round numbers as discount speeds is established as a social norm, officers may further try to avoid looking too meticulous by citing motorists at non-prominent speed levels such as 11 or 17.

Lastly, one may think of the possibility that the bunching of tickets arises due to some other behaviors than speed discounting, such as over-reporting or random rounding. Note, however, that there is no explicit incentive for officers to over-report the speed to 10. Over-reporting to 10 does not increase the fine amount, It might just provoke motorists unnecessarily even though they have no monetary reason to get upset. To the extent to which over-reporting exists in a racially-biased manner (e.g., white officers over-report white drivers' speed because of their racial prejudice), our estimates will be attenuated. It seems more plausible that those motorists who drive under 10 are overlooked by officers, except in special circumstances like school zones.

It is possible that some officers randomly round the speed up or down to the nearest round number. If so, our estimates will be also attenuated, making it difficult to discern any systematic disparity. In addition, our findings above suggest that random rounding should not be prevalent enough to yield such a massive clustering of tickets. Suppose that officers round the speed to the nearest round number, just because such numbers are cognitively less costly to assign. In this case, officers' and motorists' characteristics should not differ significantly between 10 and the nearby speeds.

4 EMPIRICAL STRATEGY

4.1 Validity of the Proxy Variable

The discussion in the previous section suggests that most of the motorists who were ticketed at exactly 10 are likely to be those who actually drove at a higher speed but received speed discounting. As long as this is true, the indicator of whether a motorist gets ticketed at 10 or not can be a proxy variable for the ticketing officer's leniency toward the motorist.

We will explain the conditions under which the proxy variable is valid. Formally, let S denote the miles above the speed limit reported, and let S^* denote the *actual speed* above the speed limit in miles. Then, we want to know whether or not the motorist gets speed discounting, that is, whether $S < S^*$. For $S \geq 10$, we have:

$$\Pr(S < S^*) = \Pr(S = 10)\Pr(S < S^*|S = 10) + \Pr(S > 10)\Pr(S < S^*|S > 10). \quad (1)$$

The problem is that the true speed is not observable. Thus, we use the proxy variable of whether $S = 10$ or $S > 10$. The proxy variable is "exact" if:

$$\Pr(S < S^*|S = 10) = 1 \text{ and } \Pr(S < S^*|S > 10) = 0. \tag{2}$$

The first condition is violated when there are motorists who were actually travelling at 10 and got ticketed at the exact speed (Type I error). The second condition is violated when there are motorists who got cited at a speed level above 10 (e.g. 11 or 12), while driving faster than that speed (Type II error). We believe that if there is any misclassification bias, it should be minimal. The case of Type I error should not be significant, given the massive spike at 10, with hardly any tickets at 9, and a rather small proportion of tickets at 11. It is likely that most drivers who actually drive at 10 just get warned.[12] The latter case of Type II error should also be negligible, since officers would presumably not use non-prominent speed levels such as 11 or 12 once they decided to be lenient.

To further ensure the validity of the proxy variable, we restrict our sample to 1) tickets cited at a speed level between 10 and 14, or, more strictly, 2) tickets cited at either 10 or 11. Due to the massive spike at 10, the first restricted sample still retains a majority of tickets (55%). The sample selection makes it difficult to extrapolate our findings to situations involving high speeders. It is indeed one of the main lessons of this paper that officers can behave differently depending upon the types of people they deal with and the contexts they work in. Despite this limitation, there are two rationales for our sample restriction. First, since our purpose is to identify officers' discretionary behavior as distinctly as possible, we want to minimize motorists' heterogeneity in terms of driving speed. In particular, in the second sample including citations at 10 and 11 only, in the absence of speed discounting, the characteristics of motorists should not differ between the two speed levels, which differ by only one mile per hour. Thus, in this restricted sample, the infra-marginality problem, although not completely avoided, is minimal. Second, it is reasonable to assume that officers are less likely to give a break to motorists driving 15 or faster. Thus, excluding those high speeders from our analysis should not bias our estimates seriously. Even if they give speed discounting to these aggressive speeders, the discounted speed is more likely to be a nearby round number such as 15 or 20. We will also show that our results are robust to extending the sample to cover speeders up to 19 (about 85 percent of all speeders).

[12] In Appendix A, following Hausman, Abrevaya, and Scott-Morton (1998), we corrected for the bias and found that the results remained the same.

4.2 Rank-Order Test of Anwar and Fang (2006)

As we explained in the introduction, we employ two empirical approaches to test for racial bias in officers' speed discounting behavior. The two alternative approaches are based on different assumptions. First, in this subsection, we modify the model of Anwar and Fang (2006) to apply their rank-order test to the question here. Although their model deals with officers' discretionary behavior in their vehicle search decisions, the model is general enough to consider any kind of officers' discretionary behavior.

The decision context in our model is whether an officer is lenient enough to give speed discounting to a particular motorist or not. Following Anwar and Fang's notation, let $t(r_m, r_p)$ denote the cost of a police officer of race $r_p \in \{M, W\}$ treating a motorist of race $r_m \in \{M, W\}$ harshly. An officer is racially prejudiced if $t(M; r_p) \neq t(W; r_p)$. In addition, there is a psychological integrity cost c of reporting a speed different from that actually observed by the officer.

Let G denote the event that the motorist will violate the speed limit again in the future if treated leniently.[13] Suppose that the officer observes a single-dimensional index $\theta \in [0, 1]$ that predicts the likelihood of recidivism.[14] Before observing θ, the officer presumes that a fraction $\pi^{r_m} \in [0, 1]$ of motorists of race r_m will violate the speed limit after being treated leniently. The index is drawn from a distribution $f_g^{r_m}$ when the driver is one of those recidivistic ones who are believed to speed again, and from a distribution $f_n^{r_m}$ when the driver is one of those who are not believed to speed in the future (i.e. the officer believes that the driver has just made an isolated mistake this time). After observing θ, the officer updates his belief about G by Bayes' rule:

$$\Pr(G|r_m, \theta) = \frac{\pi^{r_m} f_g^{r_m}(\theta)}{\pi^{r_m} f_g^{r_m}(\theta) + (1 - \pi^{r_m}) f_n^{r_m}(\theta)}. \tag{3}$$

For simplicity, we assume that if the motorist is treated harshly (i.e. no speed discounting), the probability *decreases* by a factor $\delta \in [0, 1]$. The officer's decision as to whether to treat the motorist harshly or leniently, conditional on ticketing, is as follows:

[13]It is uncertain, in reality, how much officers' ticketing and speed discounting decisions depend on the likelihood of recidivism. It seems reasonable to assume that officers punish recidivists or repeated violators more harshly. However, we suspect that they decide on the degree of punishment based on their *expectations* about recidivism, besides the issue of whether the practice is legitimate. It is even questionable whether it is possible for officers to predict drivers' future behavior.

[14]One may think of this index as a weighted sum of the actual speed and an index of the motorist's characteristics, such as their driving record and attitude. These are unobservable to the econometrician.

$$\max\{\underbrace{T - \Pr(G|r_m, \theta) - c}_{\textit{Lenient Treatment}},\ \underbrace{T - \delta \Pr(G|r_m, \theta) - t(r_m; r_p)}_{\textit{Strict Treatment}}\}, \tag{4}$$

where $T \in [0, 1]$ represents a fixed benefit of ticketing. The officer will treat the motorist harshly if $t(r_m; r_p) - c > (1 - \delta) \Pr(G|r_m, \theta)$. Anwar and Fang showed that there exists a threshold $\theta^*(r_m; r_p)$, given c and δ.[15]

Given the above model, we are ready to apply the rank-order test of Anwar and Fang. We follow their re-sampling method to ensure that officers of a given race are assigned to different districts within Boston with equal probabilities. First, given the threshold strategy, we can test for officers' monolithic preferences ($t(r_m; W) = t(r_m; M)$) by testing the equality of the average probability of being strictly (or leniently) treated across officer races for any given driver race. Second, as Anwar and Fang show, the model predicts that if none of the police officers are racially biased, the rank order of the average probability between officer races should be independent of motorist races. We will present the results of both tests in Section 4.1.[16]

4.3 Difference-in-Difference Regression Analysis

The DD estimation method is often used in the literature as an empirical strategy for testing for racial bias (Price and Wolfers, 2007; Antonovics and Knight, 2009). This approach is intuitively appealing. Suppose that officers treat drivers differently according to their race, even though they have committed similar offenses. This finding by itself is already highly suggestive of racial bias, but it is still possible that officers utilize drivers' races to infer additional hidden criminality. The DD method excludes this possibility by comparing the disparity by officers' race. The variation in the disparity by officers' race may well indicate the presence of racial bias among officers. The key assumption here is that there is no racial difference in terms of the underlying offenses and that officers deal with similar groups of drivers.[17] Since the DD approach lacks a behavioral model, it requires a careful empirical

[15] If the officer's benefit from warning is normalized to zero and the officer's maximum benefit from ticketing is less than zero, then the officer will just warn the motorist. Thus, such motorists, who look favorable to the officer, are likely to get warned rather than ticketed.

[16] Since the "success rate" (i.e. where the motorist will not violate the speed limit again due to the strict treatment) is not observable, we implement the test only for the decision regarding speed discounting. For the same reason, we cannot apply the hit rate test developed by Knowles, Persico, and Todd (2001).

[17] Fang and Persico (2009) show that the DD test is not valid if treators (i.e., officers) face different capacity constraints. Even in this case, a necessary condition is that drivers are different on the unobservables by race.

set up to ensure that drivers are similar in unobservable characteristics.

Specifically, we estimate a linear probability model, where the dependent variable is the dummy variable of whether a motorist gets ticketed by an officer at exactly 10 or not, conditional on the motorist getting ticketed and the reported speed being between 10 and 14:[18]

$$
\begin{aligned}
&1(S = 10|\mathbf{X},\ 10 \leq S \leq 14,\ T = 1) = \\
&\beta_0 + \beta_1(Motorist) + \beta_2(Officer) + \beta_3(Environment) + \beta_4(Racial\ Interactions) + u,
\end{aligned} \tag{5}
$$

where T is a dummy variable that equals one if a ticket is issued to the motorist, and zero otherwise. The variable u is the standard error term. All variables in Table 2 are included in $\mathbf{X}$; that is, motorist characteristics including race (*Motorist*), officer characteristics including race (*Officer*), and contextual characteristics, such as time and location (*Environment*). Lastly, of particular interest to us are interaction terms between officers' and motorists' races (*Racial Interactions*).

Note that if officers are strict and always report the actual speed, then the above equation will only account for motorists' driving behavior within the speed range from 10 to 14. If officers' characteristics and the racial interaction terms are uncorrelated with unobserved motorist characteristics, both β_2 and β_4 should be insignificant. Since this is critical to our identification, we will check this assumption in more detail later.

There are two dummy race variables for motorists, African-American and Hispanic (Whites are excluded, being the base group). The interpretation of these variables is twofold; on the one hand, they capture racial differences in motorists' tendency to speed, if any.[19] If motorists of a specific race tend to drive faster, they are less likely to get ticketed at 10, which is the lowest speed within the range from 10 to 14. On the other hand, the two variables may capture officers' preemptive deterrence efforts or the monolithic racial preferences of

[18]We also estimated a Probit model and computed marginal effects, following Ai and Norton (2003). The results remained the same. We prefer the linear probability model, because any bias due to the error distribution misspecification is expected to be minimal, given our rich set of controls (Knowles, Persico and Todd, 2001), while interpreting marginal effects for the interaction terms in nonlinear models is somewhat tricky. The results are available upon request. Another alternative specification is a zero-inflated Poisson model that allows for two different data-generating processes, one for 10 and another for higher speed levels, 11–14. The results are similar.

[19]Knowles, Persico and Todd (2001) indicate that there is no significant racial difference in travel patterns and driving style. Lamberth (1996) observed 5,741 vehicles in Maryland, and found that the proportions of drivers and violators were almost equal for all races. We also assume that motorists do not change their driving style (such as speed and route) in response to officers' racially-biased enforcement.

officers of all races. The first point emphasizes the 'schooling drivers' aspect: officers may be stricter with motorists of a specific race if they believe that those motorists will be likely to speed again if treated leniently. In this case, the coefficients of drivers' races will represent $\Pr(G|r_m, \theta)$ in the model.

Two dummy race variables for officers (African-American and Hispanic) are expected to capture officers' race-specific strictness relative to white officers (the excluded base group). Note that the estimates will be biased (and underestimated in absolute terms) to the extent to which motorists can predict the race of officers they will encounter on their routes. This seems likely to be the case in Boston, because of the "Same Cop / Same Neighborhood (SC/SN)" policy of the Boston Police Department.[20] However, we expect that this kind of bias, if any, will be negligible. First, we control for neighborhood dummy variables. It is unlikely that motorists can predict the race of on-duty officers at precincts and streets within neighborhoods. Second, it is also unlikely that motorists will alter their speed or route depending on the expected race of officers, unless they carry illicit drugs, firearms, etc. To the moderate speeders in our sample, whether there will be an officer on their way should be a more pressing question than that officer's race.

The racial interaction terms are supposed to capture relative racial prejudices. The question of whether the interaction terms actually identify racial bias is a critical issue (Persico, 2009). For example, Rowe (2009) points out that if officers have different levels of strictness by their race, and if motorists have different degrees of infraction by their race, the DD method does not necessarily identify officers' racial bias.[21] This critique does not strongly apply here, mainly because our sample is a homogenous group of moderate speeders. In our narrowly-defined samples (and particularly the one including those cited at 10 and 11 only), it seems reasonable to assume that drivers are similar in terms of the underlying offenses.

Ideally, we want to include six different combinations of officers' and motorists' races, given three racial groups in our study. It is, however, impossible to estimate all six coeffi-

[20] Refer to http://www.cityofboston.gov/police/same_cop.asp. "Under SC/SN, the same beat officers are assigned to a neighborhood beat, and will spend no less than 60% of their shift in that designated beat." There are 11 neighborhoods in Boston. The neighborhood boundaries that the police use are slightly different from those of neighborhoods in our data.

[21] To see intuitively how the critique works, suppose that minority officers are stricter than white officers, and, as a result, use a lower threshold in terms of our model. Suppose that minority motorists tend to commit offenses that are more severe. In this case, even if officers are all unbiased, it would be possible to find that minority officers are relatively harsher on minority drivers.

cients, due to perfect collinearity. Thus, we need to come up with some hypothetical types of racial bias, and, accordingly, impose parametric constraints. We include the following four dummy variables: 1) racial mismatch with own-race preferences; 2) minority officer and minority motorist; 3) white motorist and African-American officer; and 4) African-American motorist and white officer. These variables are motivated either by the literature or empirically by our data. Note that all four forms of racial bias may coexist.

As mentioned earlier, the DD method allows us to address the sample selection problem.[22] Note that the above model deals with speed discounting conditional on officers' decisions to issue tickets, $T = 1$. We use data on warnings recorded for the first two months of the data, April and May, 2001. Using this subsample, we jointly estimate the following selection model with Equation (5):

$$\begin{aligned}&\Pr(T=1|\mathbf{X},\ 10 \leq S \leq 14) = \\ &\Phi[\gamma_0 + \gamma_1(\mathit{Motorist}) + \gamma_2(\mathit{Officer}) + \gamma_3(\mathit{Environment}) + \gamma_4(\mathit{Racial\ Interactions})].\end{aligned} \tag{6}$$

We cannot *a priori* exclude certain variables from the equation for speed discounting, so after trying different specifications of the selection model, we decided to use two squared terms of speed limit and age as excluded variables. In addition, as suggested by Makowsky and Stratmann (2009), we exclude the variable for a commercial driver's license from the primary equation. All of the excluded variables turned out to be insignificant in the primary equation when we estimate the selection model without the excluded variables.

5 EMPIRICAL RESULTS

5.1 Who Gets Speed Discounting from Whom?

We present our empirical findings beginning with the rank-order test results in Table 2. First, we use the Pearson χ^2 test to test for officers' monolithic preferences. We strongly reject the null of officers' monolithic behavior for all motorist races; if officers have monolithic preferences, all races of officers should treat the motorists of the mutually most-preferred race more leniently, and the variables for the motorists' race should reveal the officers' preference ordering, if any. However, the speed discounting rates differ among officer racial groups for

[22] The existing models in the vehicle-search literature consider officers' searching behaviors conditional on stopping. Persico (2009) points out that developing models of multi-stage treatment is a future research topic.

a given group of motorists. In particular, African-American officers are significantly less likely to give speed discounting, while white officers are more likely to be lenient to minority motorists than minority officers are. For all three races of motorists, the p-values are less than 0.001.

Second, we also reject the null hypothesis of no relative racial prejudice. For a given race of motorists, the rank order over the discounting rates across officers' racial groups depends on the race of motorists. Specifically, for white motorists, we cannot reject the equality between white and Hispanic officers (the z-statistic is 0.2), while white officers exhibit higher discounting rates for African-American and Hispanic motorists than African-American or Hispanic officers do.[23] The test suggests that at least one racial group of officers is racially biased.

Table 2 also shows the results from the DD estimation without control variables. First, we find that white officers are more likely to give speed discounting and that white motorists are more likely to receive speed discounting. For all three races of motorists, African-American officers are stricter than other-race officers in terms of speed discounting. Second, the diagonal three estimates in the lower right panel are the DD estimates. When we separately examine the two minority groups, African-Americans and Hispanics, we find that African-American officers are 6.6% points less likely to give speed discounting to African-American motorists and that Hispanic officers are 17% points less likely to give speed discounting to Hispanic motorists. Hispanic officers are much stricter to motorists of their own race, but they treat white motorists as favorably as white officers do. On the other hand, African-American officers are less lenient to white drivers than white officers are. When African-American and Hispanic officers are put together into one minority group, we find that minority officers are 13% points less likely to give speed discounting to minority motorists. The estimates are all significant at the 1% level.

Table 3 presents the regression results with control variables. By controlling for a rich set of variables representing officer/motorist characteristics, and the contexts in which citations are issued, we check whether our results are driven by observable differences across pairs of officer and motorist races. We examine tickets between 10 and 14 in Column 1. In Column 2, the sample is further restricted to tickets cited at 10 and 11 only. Column 3 includes all tickets issued from 10 to 19. In the last two columns, we implemented "placebo tests" in

[23] We also rejected the hypothesis that white officers exhibit the same discounting rate for white and minority drivers.

order to check the validity of our identification strategy for exploiting the massive clustering of tickets at 10. In Column 4, after restricting the sample to tickets between 11 and 14, we estimate the same model with a different dependent variable, indicating whether the ticket is cited at exactly 11. Note that this new dependent variable, which we call a "fictitious proxy" variable, does not represent speed discounting, since officers do not use 11 as a discounting speed. The model will instead reflect the actual speed distribution. However, the distribution could still be distorted by speed discounting, as it includes only those who did not get speed discounting. Thus, the model may also reveal differences between "the impact of speed discounting to 10 on tickets of 11" and "the impact of speed discounting to 10 on tickets of 12–14". For example, if officers are more likely to lower the speed from 11 to 10 than from 12 to 10 for certain motorists (e.g. females), we should find relatively fewer tickets issued to those motorists at 11 than at 12. In Column 5, we further restrict the sample to 12–14 and use the dependent variable of whether the ticket is cited at 12.

The first noteworthy finding in Columns 1 and 2 is that all of the motorists' characteristics are insignificant. This is not surprising, since motorists are likely to be homogenous as moderate speeders in the relatively narrow speed range of 10–14 or 10–11.

Unlike motorists' characteristics, however, officers' characteristics turn out to be significant. First, male officers are significantly (32% points) more likely to issue tickets at exactly 10. The magnitude of this gender gap is substantial, so much so that we can even consider speed discounting as basically a male-officers' behavior. Second, we find that less experienced officers are more likely to give speed discounting. One possible explanation is that segments of police officers who can get away with speed discounting more easily commit to it more often. Males constitute the much larger gender group in the police force, and newer, younger officers can easily be forgiven for their mistakes, given their relative rookie status. Alternatively, due to career concerns, newer officers might want to minimize the possibility that they get into trouble by being accused by motorists. Male officers' lenient behavior might also reflect gender differences in personality. Third, we find that the more violations motorists have, the less likely officers are to give speed discounting. Each extra violation decreases the probability of being ticketed at 10 rather than at a speed level between 11 and 14 by 3.5% points.

Regarding officers' race, we find that minority officers are significantly less likely than white officers to give speed discounting. African-American and Hispanic officers are respectively about 12% and 8% points less likely to give speed discounting than white officers. It is interesting to find that officers who are in a minority status within the police force, including females, African-Americans, and Hispanics, are less lenient. One plausible explanation for this is that these minority segments within the police force cannot easily get away with any mistakes, and may feel the need to prove themselves to the largest (and culturally and administratively dominant) group in the police force, namely the white-male officers. We will discuss this aspect further in Section 6.

Among the racial interaction terms, two variables are significant in Column 1; one between minority officer and minority motorist, and the other between white motorist and African-American officer. Minority officers are about 14% points less likely to give speed discounting to minority motorists than white and Hispanic officers are. African-American officers are also 8% less likely to give speed discounting to white motorists than white and Hispanic officers are. African-American officers are much less lenient to all motorists than other officers are; however, they are even less lenient to minority motorists than they are to white motorists. The difference is marginally significant ($p = 0.095$).

The results in Column 2 are similar to those in Column 1. We find that most estimates weaken in magnitude but still remain significant, except that the interaction term for African-American officer and white motorist becomes insignificant. In this subsample where we define our proxy variable in the most stringent way, African-American officers are indeed harsher to minority drivers than they are to white drivers. The results change little when we include all tickets up to 19 in Column 3.

In Columns 4 and 5 using the fictitious proxy variables, we find that most variables turn out to be insignificant. However, the dummy variable for African-American officers is significant and reversed in sign (positive). This means, as explained before, that there are relatively more tickets issued by African-American officers at 11 (or 12) compared to higher speed levels, 12–14 (or 13–14). This is presumably because white and Hispanic officers tend to discount more tickets that are supposed to be cited at 11 (or 12) than those which are supposed to be cited between 12–14 (or 13–14).

Several other findings are also informative regarding officers' behavior. The effect of the speed limit is significantly positive in Columns 3 and 4, while it is significantly negative in the first two columns. The negative effect in Columns 1 and 2 is likely to be a result of the officers' perception that high speed in itself is a dangerous act and should be curbed more, with less speed discounting as the speed motorists are allowed to travel at increases. The positive effect in Columns 4 and 5 is, then, simply the other side of the coin. It is also likely to reflect the fact that, taking into account officers' less lenient ticketing in higher speed limit areas, motorists themselves may be reluctant to speed as much in those areas, and consequently may get caught and ticketed at relatively lower speeds within the speed ranges, i.e. at 11 in the 11–14 range, and at 12 in the 12–14 range.

Lastly, in Table 4, we account for officers' endogenous choice of whether to issue a ticket or a warning using the sample selection model. In the selection equation, we find that minority officers are 24.5% points more likely to issue tickets rather than warnings to minority motorists. However, the term of racial mismatch also turns out to be significantly positive. We cannot reject the equality between two coefficients, suggesting that minority officers are more likely to issue tickets than white officers. After correcting for selection, we have a stronger result for racial disparities in speed discounting; minority officers are 31% points less likely to give speed discounting to minority motorists.

5.2 Robustness across Different Subsamples

In this subsection, we check our main finding's robustness to various officer and motorist characteristics. Table 5 presents the results for the minority-minority interaction term across different groups of officers and motorists. We find that the results are quite consistent across different officer groups. Both experienced and inexperienced minority officers are harsher on minority motorists, though the result is stronger for newer officers. Also, the result holds regardless of whether officers issue speeding tickets frequently or not (those who have issued 100 tickets or more versus others), although the result appears to be stronger among infrequently-ticketing officers.

The results are also consistent across different types of motorists. We find, across the board, that minority officers are harsher to minority drivers, but the estimates' statistical significance and magnitude vary. First, we find that minority officers are harsher to *male* minority motorists, while we find a slightly weaker, insignificant estimate for female motorists. Second, the results are similar between day and night (6 pm to 6 am), though the disparity becomes stronger at night. Third, minority officers are harsher to minority motorists driving relatively old vehicles (aged more than 5 years). The result is weak and insignificant for those with newer vehicles. Lastly, we examine whether the results change across different neighborhoods. We define neighborhoods with 60% or more white population as "white neighborhoods", and those with 20% or more African-American or 20% or more Hispanic populations as "minority neighborhoods." We find that, particularly in the minority neighborhoods, minority officers are harsher to minority motorists. The result is weak and insignificant in white neighborhoods. The lack of significance in this case, however, might be because of the relatively few observations of minority officers and minority drivers interacting in white neighborhoods.

As a further robustness check, we control for motorists' home zip code. Controlling for zip codes should reduce the unobserved heterogeneity in motorists' characteristics, given a relatively small population size for a single zip code and the degree of socioeconomic homogeneity within the area. Table 6 shows that this strengthens our results; minority officers are 14% points less likely to give speed discounting to minority motorists. Second, we exclude tickets issued when vehicle searches were conducted to address the possibility that officers could behave differently when they think they are dealing with potential criminals. We find that our main result still holds with this sample.

Next, we examine African-Americans and Hispanics separately.The results are consistent across all combinations. It is found that minority officers do not differentiate between African-American and Hispanic motorists (that is, African-American and Hispanic motorists are treated equally harshly). We reject the hypothesis that African-American officers are as strict to minority drivers as Hispanic officers. At this point, it is interesting to recall that Hispanic officers are significantly underrepresented in the Boston police department.[24]

Lastly, we exclude African-American officers as well as African-American drivers. The main concern we want to address here is that African-American officers are quite different from others. It seems that African-American officers are more likely to patrol on local streets. The proportion of in-town drivers among those ticketed by African-American officers is 56 percent as compared to 46 and 40 percent for white and Hispanic officers, respectively. The average speed limit is also slightly lower for African-American officers (30.9 m.p.h.) as compared to 31.8 and 31.6 for white and Hispanic officers. Also, African-American officers are more experienced than others. On the other hand, white and Hispanic officers are quite comparable in terms of observable characteristics. The results in Column 4 of Table 6 confirm

[24]This would vary between places and over time. The Alpert Group (2004), which reviewed the traffic stop practices of the Miami-Dade Police Department, report that "differences in the treatment of whites and Hispanics were . . . minimal" (p. vii). In Miami, Hispanics constitute 62% of the population, African-Americans 20%, and whites 18%.

that Hispanic officers are harsher on Hispanic drivers.

5.3 Unobservable Motorist Characteristics and the Nonrandom Deployment of Officers

Despite our rich set of control variables, we obviously do not observe all of the information about motorists that police officers take into account when they decide whether to give motorists a break or not. The most important unobserved motorist characteristic is the driving record. Thus, in this subsection, we examine how this omission could bias our estimates. The question is whether minority motorists who get ticketed by minority officers are more likely to have a bad driving record.[25] This concern is legitimate, in that minority officers are assigned to neighborhoods in such a way that they are statistically more likely to come across such minority motorists. In particular, Boston police officers tend to be assigned to those districts in which more people of their own racial group reside. Thus, minority officers are more likely to meet minority motorists because they patrol minority residential areas more frequently. If minority motorists in minority neighborhoods are more likely to have bad driving records, then our estimates will be biased.

We think, however, that this should not be a real problem in our study, first of all because we have already included 10 neighborhood dummy variables. If minority motorists in minority neighborhoods tend to have a bad driving record, white and minority officers working in these areas should both be equally likely to meet such bad-type motorists. Furthermore, it is not true in our restricted sample that minority drivers are more likely to be ticketed by minority officers in minority neighborhoods. In minority neighborhoods, 73% of minority motorists are ticketed by white officers. In white neighborhoods, about 50% of minority motorists are ticketed by white officers.

Still, our estimates could be biased if minority officers are assigned to specific streets or districts within a neighborhood where minority motorists have a bad driving record compared to white motorists. It is, however, hard to believe that officers are instructed about their patrol areas so specifically. As will be elaborated later in Section 6, the finding that minority officers voluntarily concentrate on those particular areas within minority neighborhoods does not contradict our conclusion in this paper.

[25]Conversely, you might ask why white motorists who get ticketed by minority officers are less likely to have bad driving records. It is *a priori* uncertain which question is the more appropriate one to ask.

5.4 Fine Discounting and Multiple Citations

Makowsky and Stratmann (2009) examine officers' *fine discounting*, that is, where officers charge a lower speeding fine than is expected from the statutory formula. This kind of discounting can either substitute for or complement the speed discounting that we examine in this paper. If it acts as a substitute, our results might be misleading, since it is possible, for example, that minority officers might compensate minority drivers by giving smaller fines. To address this issue, we examine how motorists' and officers' race variables determine the speeding fine. We use two alternative measures of fine discounting as the dependent variable: the first is whether officers impose a lower amount than expected, given the cited speed, and the second is the gap between the actual fine amount and the statutory amount, conditional on the cited speed. The specification is similar to our basic equation, except that we include the cited speed as an additional conditioning variable. For both measures of fine discounting, we found that the coefficient of the minority-minority interaction term is insignificant (but negative).[26] This suggests that there is no significant minority-to-minority disparity in terms of monetary discounting. This makes sense, in that fine discounting is more visible to a third party, such as the state government or any supervising agent, while officers can always give the same amount of discounting by speed discounting.

Yet another possible channel of the police discretion is overlooking some additional violations, such as driving with an expired registration. In our sample, about 30 percent of drivers who were cited for their speeding violation received additional citations. About 26 percent received one additional citation and 4 percent two additional citations. There is one case where the driver received 8 citations at once. The results not presented here show that none of the racial interaction terms is significant.

5.5 Unrecorded Stops

In this subsection, we deal with our last econometric concern. One major disadvantage of the Massachusetts traffic data is that it does not record every vehicle stop. This is potentially a problem for our estimation, because officers may let certain motorists go without even a written warning, which the econometrician cannot observe at all. This sort of *data censoring* might bias our estimates of the racial interaction terms, but only under very restrictive conditions. Suppose that minority officers stop vehicles, and, after finding out that the

[26]Complete results are available from the authors.

motorists are minority, only cite those with negative traits. Also suppose that minority officers do not treat white motorists differentially according to such characteristics, and, additionally, that white officers do not use any such criterion, regardless of motorists' races. In unlikely cases like this, the estimate of the minority-minority interaction term will be biased and capture unobserved motorist characteristics.

We can test whether minority officers are indeed more selective in citing drivers than white officers. Specifically, we examine the total number of citations. The idea is that even though we do not observe the number of motorists an officer let go, we do observe how many tickets the officer issued per day. Also, it is reasonable to assume that the more selectively officers choose whom to cite, the fewer citations they will be able to issue tickets for per day. This suggests the following estimation equation:

$$\begin{aligned} N_{ijkt} &= \alpha_0 + \alpha_1(\textit{Motorist Races}) + \alpha_2(\textit{Officer Races}) + \alpha_3(\textit{Racial Interactions}) \\ &+\alpha_4(\textit{Number of Officers}) + (\textit{Neighborhood FE}) + (\textit{Day FE}) + u_{ijkt}, \end{aligned} \tag{7}$$

where N_{ijkt} is the total number of tickets (or all citations including written warnings) issued by officer race group i to motorist race group j in neighborhood k on day t. Since there are three racial groups each for officers and drivers, 11 neighborhoods, and 605 days, the maximum number of group-cell observations is 59,895. Each cell is defined by the quadruplet $ijkt$.

The main variable of interest here is again the interaction term between minority officer and minority motorist. To disentangle it from other confounding effects, we include some control variables. First, we include the dummy variables for motorists' races. Since there are fewer minority motorists in the driving population, it is not surprising to find fewer tickets being issued to them. Second, we include the number of officers in each group cell, since there should be more citations when there are more officers. Lastly, since the volume of traffic and the number of speeding vehicles vary across time and space, we add individual neighborhood and calendar-day fixed effects (FE). The neighborhood fixed effects are included because minority officers have a higher chance of encountering minority motorists in minority neighborhoods.

Table 7 shows the results. Contrary to our concern, we find that minority officers issue more tickets to minority motorists. In an average day, minority officers issue about 0.3 additional tickets or 0.5 additional citations (including written warnings) to minority motorists than to white motorists. This result is found in both white and minority neighborhoods. This is in harmony with our previous findings regarding speed discounting.

5.6 Magnitude of Speed Discounting

So far we have focused on the *incident* of speed discounting ignoring the magnitude of speed discounting, say, $S^* - 10$. This is because we do not observe the actual speed (S^*). One might raise a concern since it is possible minority officers are less likely to give speed discounting to minority drivers but, once they do, they give larger discounts. We have two reasons why we believe our results are valid despite the data limitation. First, it is difficult to explain why officers would distinguish the incident of speed discounting and its magnitude. Second, the incident of speed discounting is more relevant for the purpose of identifying a bias against a certain group. We are interested in finding how likely it is that a typical driver in a racial group is leniently treated. The magnitude of speed discounting is informative of the degree of officers' selectivity within a racial group.

6 DISCUSSION: MINORITY OFFICERS IN THE POLICE FORCE AND VIS-À-VIS MINORITY MOTORISTS

The findings in this paper are somewhat unusual, in that, in the rest of the economics and criminology literature, racial disparities in law enforcement are explicitly or implicitly associated with the discriminatory behavior of white officers against minority people or vice versa.[27] To understand our finding that minority officers are relatively harsher to minority motorists, we begin by asking the following two complementary questions. First, why do minority officers *prefer* to treat minority motorists more strictly? Second, is it actually the minority motorists who provoke minority officers to be strict? The objective of this section is not to find definite answers to these questions, but at least to explore probable causes.

Relative to the first question, we need to investigate minority officers' preferences, and,

[27] For example, Donohue and Levitt (2001) show that an increase in the fraction of minority officers in a city's police force increases the arrests of whites, but has little effect on the number of arrests of non-whites. Likewise, an increase in the white-officer composition of the police force leads to an increase in the number of arrests of non-whites, but has no impact on the arrests of whites. However, few studies have indeed found that minority officers are harsher on minority people in other fields of law enforcement. For example, Brown and Frank (2006) found that African-American suspects are more likely to be arrested when the arresting officer is an African-American.

more fundamentally, ask why and how such preferences are formed. First, we notice that minority officers' strictness against minority motorists is – at least seemingly – not consistent with own-race preferences. It has been found that minority people, particularly African-Americans, have a strong racial identity and strong own-race preferences (Fryer and Levitt, 2004; Fisman et al., 2008). In-group favoritism (and the implied out-group un-favoritism – or prejudice – directed against people who are not in their group) is a theoretically grounded and central concept in social psychology (Tajfel and Turner, 1979). Indeed, the issue in the debate concerning racial profiling in the vehicle-stop-and-search literature is why cross-race disparities, if any, are observed (or felt by the public), and whether officers are racially prejudiced. Thus, it seems that this concept of cross-racial prejudice cannot by itself directly explain our finding (although they might be deeply related at another level, as we will elaborate later).

Thus, we start by focusing on minority officers' status within the police force, as well as the monitoring and incentives they are subject to. A particular segment of officers may monitor others in the police force, just as in any other organization. The original purpose of monitoring should be to enhance the efficiency of the organization. However, suppose that this monitoring segment constitutes a larger fraction of the police force, and the monitored segments, which may already have a lower political and economic power in the society, comprise a smaller fraction of the police force. These factors may make the latter groups' status in the police force less advantageous.

Indeed, many interview-based studies have revealed that minority officers frequently feel racial hostility inside the force and have the day-to-day experience of being an outsider – being constantly tested and monitored – within the police subculture.[28] Minority officers are often perceived to be less able than white officers by their colleagues, as well as by other people; they "must constantly prove themselves worthy to the many whites who view [them] as unworthy" (Bolton Jr. and Feagin, 2004, p. 105). They are also more likely to experience negative social interactions with their supervisors and co-workers (Morris, 1996). Dedman and Latour reported that minority officers desire to be "accepted", and, for that purpose, they do not want to "go easy", particularly on minorities. An African-American officer said, "we are being watched as not only an officer, but also a black officer" (Bolton Jr. and Feagin,

[28]This might be a universal phenomenon. In a classroom context, Bowen (2009) found that "students who experience critical mass by never being racially isolated in the classroom encounter the least amount of overt racism and stigma."

p. 112). Although there may be other possible explanations, our findings in this paper are overall consistent with the above argument of the disadvantaged status and monitoring of minority officers within the police force.

Equally reasonably, minority officers may want to change negative stereotypes about their own racial group. This is reasonable, because those stereotypes, whether they are substantiated or not, constitute one of the fundamental causes of their underprivileged status within the police force.

Alternatively, they might well feel more responsible for or concerned about their own communities' problems. This is also in harmony with the casual observation that minority community leaders often call for harsh law enforcements because they are more easily blamed than whites. In this case, the minority officers' behavior that we found, if it is motivated by their emotional attachment to their own racial group, is not inconsistent with own-race preference and positive racial identity.

In this sense, it is interesting to note that the minority-on-minority disparity is stronger with Hispanic officers. The ethnic identity problem seems more complicated for Hispanic officers, since they are usually second- or third-generation immigrants. As Irlbeck (2008) finds, while most Hispanic officers still exhibit a strong cultural attachment to the Hispanic community, a number of them self-identify as white. In addition, unlike earlier waves of Hispanic immigrants, new Hispanic immigrants have been arriving from a variety of different countries. These factors may prevent them from forming a unified racial identity and own-race preferences as strong as that which the African-Americans have formed. At this point, it is interesting to recall that Knowles, Persico and Todd (2001) only found a racial bias against Hispanic motorists.

Regarding the second question posed in the beginning of this section, it is conceivable that the minority-on-minority disparity might be caused by drivers' behaviors in the first place. Looking at the drivers' side is somewhat unusual; the racial profiling literature attempts to explain any observed racial disparities solely based on officers' behavior.[29] This approach is reasonable, in that it is officers who make decisions and take actions; the relationship between officers and the public is hierarchical, so people are not in a position to argue against officers, and particularly in serious situations like vehicle searches where more is at stake for both sides. However, in the case of minor offenses such as moderate speeding, it seems plausible

[29] Anwar and Fang (2006) point out the possibility that motorists' behavior depends on the races of officers.

that the stopped drivers might more easily dare to disagree with officers, complain, and thus, in effect, ask for a harsher punishment.[30] For example, Engel et al. (2006) find that after holding various factors constant, disrespectful, non-compliant, and resistant drivers are more likely to be searched. The question is whether minority motorists are more likely to provoke minority officers despite the possible adverse consequences to themselves of such behavior, and, if so, why.

Defiant behavior on the part of minority motorists would become plausible if one took into consideration the fact that minority drivers may have different preferences about minority officers. Basically, it is likely that minority motorists may dare to start arguing with minority officers because they may feel closer to officers of their race, at least in social hierarchy and/or culture, and this more (social-hierarchical and/or cultural) comfortable position may prompt them to dare to talk back to these officers. Somewhat ironically, this social-hierarchical and/or cultural closeness might in turn provoke officers' unfavorable reactions: "[a] large proportion of black police officers reported that they commanded more respect from white citizens than from black citizens" (Bolton Jr. and Feagin, 2004). Of course, one should keep in mind that officers, being trained professionals, should not be affected emotionally by drivers' behavior if it is irrelevant to efficient or fair law enforcement; such desirable professionalism, on the other hand, can be expected to be stronger in the case of more experienced officers (which is supported by our empirical results as well).

Alternatively, it is possible that minority drivers feel disappointed or even betrayed when they are treated harshly by officers of their own race. "[S]ome members of black communities perceive them to be traitors" and "most of [the] officers also reported that they did not live in the community they worked in" (Bolton Jr. and Feagin, 2004). Minority officers are therefore dissociated from their own community, not only because they are police officers, but also because they belong to a different socioeconomic class (Leinen, 1984, p. 177).

7 CONCLUSIONS

Speed discounting–as a form of police discretion, just like oral and written warnings–has always been a prevalent phenomenon, but, to the best of our knowledge, it has never before been empirically examined in the growing economics and criminology literatures regarding

[30]Ridgeway (2006) found that black motorists tend to have longer duration of vehicle stop, although it is unknown whether this is due to officers' intentional tardiness or motorists' complaining.

the discretionary behavior of police officers. Studying racial biases in the speed-discounting context adds a new and, to a large extent, unexpected dimension to the racial profiling literature. Our findings suggest that officers are racially biased in speed discounting, and, furthermore, minority officers are relatively harsher to minority drivers. There are two main implications of our findings. First, officers' racial biases can arise in different forms and for various reasons. It does not necessarily mean discrimination against minority drivers by white officers. Second, officers may behave differently in different tasks, from ticketing to vehicle searches. This might be because they deal with different types of people in different contexts.

Although one might consider racial discrimination in the context of speed discounting as a relatively minor issue compared to discrimination in the context of vehicle stops and searches, it is more relevant to most people everyday. Perhaps it is a unique context in which to study interactions between police officers and a fairly large number of motorists. In addition, the triviality of speed discounting from the perspective of officers may help us to identify racial bias better. Broadly speaking, our identification approach is in the same spirit as the recent literature focusing on "implicit discrimination", in that, given substantial social attention, racial bias will be probably be revealed more when people are less cautious.[31] It is likely that officers seriously consider the potential consequences of their behavior in high-stake situations like vehicle searches. In this case, racial bias might well appear more openly in low-stake and high-discretion situations.

A natural question is whether there should be any public policy to fix the racial bias we have found in this paper. This is a difficult question, because our findings indicate neither a mutual racial discrimination between different races nor a discrimination against one particular race by all other races. Instead, it is the minorities – be it those in the police force or those on the streets as drivers – who seem to suffer at each other's hands. The minority-on-minority disparity may to some extent be a consequence or symptom of the current relative political and economic power of different segments. Racial diversity in the police force could be increased to make hierarchical monitoring less lopsided; then again, this

[31]The basic idea of this new approach is that racial prejudice is likely to be implicit and even unconscious (Bertrand, Chugh, and Mullainathan, 2005). One empirical implication of this is that racial bias might be revealed only under split-second situations. Price and Wolfers (2007) examine racial bias in NBA referees' foul calls, which occur in a couple of seconds. They find that referees call fouls more frequently on players of the opposite race. Plant and Peruche (2005) find that, in computer simulations where they have to take action within seconds, police officers are more likely to mistakenly shoot African-American suspects than white ones, although this bias was eliminated after extensive training.

may not prove very useful, as we have seen a potential cultural conflict between Hispanic officers and Hispanic people. In the short run, small changes, such as the use of more air patrols and speed cameras, may be helpful. They can be effective in both curbing speeding and reducing vehicle accidents, as well as in detecting racial bias and restoring the social trust of minority people toward police officers.

Lastly, to shed better light on this issue, one also needs to collect more data on interactions between officers and motorists during ticketing stops,[32] as well as on motorists' driving records – not to mention more data from other parts of the country, where the racial compositions of the population and the police force favor different types of minorities more. The latter attempt in particular would be significant if one's ultimate objective were not only to detect racial bias, but also, if it exists, to find a solution to the issue. To find any such solution, as our findings in this paper suggest, one needs to understand the self-identity of different groups of officers, as well as the police's internal governance structure in other parts of the country where the racial compositions of the population and the police force favor different races of officers. This could potentially be an important area for future research.

[32] For example, the Miami-Dade Police Department used trained observers to ride with police officers (The Alpert Group, 2004). While this data collection method would deliver additional information about police-driver interactions, it may be intrusive as well as costly.

References

Ai, Chunrong and Edward Norton. 2003. "Interaction Terms in Logit and Probit Models." *Economics Letters*, 80(1): 123-129.

Antonovics, Kate L. and Brian G. Knight. 2009. "A New Look at Racial Profiling: Evidence from the Boston Police Department." *Review of Economics and Statistics*, 91(1): 163-175.

Anwar, Shamena and Hanming Fang. 2006. "An Alternative Test of Racial Prejudice in Motor Vehicle Searches: Theory and Evidence." *American Economic Review*, 96(1): 127-151.

Bertrand, Marianne, Dolly Chugh, and Sendhil Mullainathan. 2005. "Implicit Discrimination." *American Economic Review Papers and Proceedings*, 94-98.

Blalock, Garrick, Jed DeVaro, Stephanie Leventhal, and Daniel H. Simon. 2007. "Gender Bias in Power Relationships: Evidence from Police Traffic Stops." ILR Collection Working Papers, Cornell University.

Bolton Jr., Kenneth and Joe R. Feagin. 2004. *Black in Blue: African-American Police Officers and Racism*. New York: Routledge.

Bowen, Deirdre M. 2009. "A Brilliant Disguise: An Empirical Analysis of the Colorblind Ideal in a Post Affirmative Action World." Seattle University School of Law, Mimeo (http://works.bepress.com/deirdre_bowen/2).

Brown, Robert and James Frank. 2006. "Race and Officer Decision Making: Examining Differences in Arrest Outcomes between Black and White Officers." *Justice Quarterly*, 23(1): 96-126.

Clarke, Ronald V. 1996. "The Distribution of Deviance and Exceeding the Speed Limit." *The British Journal of Criminology*, 36(2): 269-281.

Close, Billy R. and Patrick L. Mason. 2007. "Searching for Efficient Enforcement: Officer Characteristics and Racially Biased Policing." *Review of Law & Economics*, Vol. 3, No. 2, Article 5 (http://www.bepress.com/rle/vol3/iss2/art5).

Dedman, Bill and Francie Latour. 2003. "Speed Trap: Who Gets a Ticket and Who Gets A Break?" *The Boston Globe*, July 20.

Donohue III, John J. and Steven D. Levitt. 2001. "The Impact of Race on Policing and Arrests." *Journal of Law and Economics*, XLIV: 367-394.

Engel, Robin S. and Jennifer M. Calnon. 2004. "Comparing Benchmark Methodologies for Police-Citizen Contacts: Traffic Stop Data Collection for the Pennsylvania State Police." *Police Quarterly*, 7(1): 97-125.

Engel, Robin S., James Frank, Rob Tillyer, and Charles Klahm. 2006. *Cleveland Division of Police Traffic Stop Data Study: Final Report.* July 7, 2006.

Fang, Hanming and Nicola Persico. 2009. "Difference-in-Difference Estimators of Prejudice: An Examination of the Existing Test and An Alternative." Presentation at the Economic Research Initiatives at Duke Conference.

Farrell, Amy, Jack McDevitt, Lisa Bailey, Carsten Andresen, and Erica Pierce. 2004. "Massachusetts Racial and Gender Profiling Study." Northeastern University, Institute on Race and Justice.

Fisman, Raymond, Sheena S. Iyengar, Emir Kamenica, and Itamar Simonson. 2008. "Racial Preferences in Dating." *Review of Economic Studies*, 75: 117-132.

Fryer, Roland G. and Steven D. Levitt. 2004. "The Causes and Consequences of Distinctively Black Names." *Quarterly Journal of Economics*, 119: 767-805.

Grogger, Jeffrey and Greg Ridgeway. 2006. "Testing for Racial Profiling in Traffic Stops from behind a Veil of Darkness." *Journal of the American Statistical Association*, 101(475): 878-887.

Hausman, Jerry A., Jason Abrevaya, and F.M. Scott-Morton. 1998. "Misclassification of the Dependent Variable in a Discrete-Response Setting." *Journal of Econometrics*, 87: 239-269.

Irlbeck, Dawn. 2008. "Latino Police Officers: Patterns of Ethnic Self-Identity and Latino Community Attachment." *Police Quarterly*, 11: 468-495.

Johnson, Edward, Nicole B. Johnson, and Devin Shanthikumar. 2007. "Round Numbers and Security Returns." Mimeo.

Knowles, John, Nicola Persico, and Petra Todd. 2001. "Racial Bias in Motor Vehicle Searches: Theory and Evidence." *Journal of Political Economy*, 109(1): 203-232.

Lamberth, John. 1996. *A Report to ACLU*. New York: American Civil Liberties Union.

Lawpoolsri, Saranath, Li Jingyi, and Elisa Braver. 2007. "Do Speeding Tickets Reduce the Likelihood of Receiving Subsequent Speeding Tickets? A Longitudinal Study of Speeding Violators in Maryland." *Traffic Injury Prevention*, 8(1): 26-34.

Leinen, Stephen. 1984. *Black Police, White Society*. New York: New York University Press.

Makowsky, Michael and Thomas Stratmann. 2009. "Political Economy at Any Speed: What Determines Traffic Citations?" *American Economic Review*, 99(1): 509-527.

McConnell, E. H. and A. R. Scheidegger. 2001. "Race and Speeding Citations: Comparing Speeding Citations Issued by Air Traffic Officers with Those Issued by Ground Traffic Officers." *Presented at the annual meeting of the Academy of Criminal Justice Sciences*, Washington D.C.

Morris, Anne. 1996. "Gender and Ethnic Differences in Social Constraints among a Sample of New York City Police Officers." *Journal of Occupational and Health Psychology*, 1(2): 224-235.

Persico, Nicola. 2009. "Racial Profiling? Detecting Bias Using Statistical Evidence." *Annual Review of Economics*, 1: 9.1-9.25.

Plant, E. Ashby, and B. Michelle Peruche. 2005. "The Consequences of Race for Police Officers' Responses to Criminal Suspects." *Psychological Science*, 16: 180-183.

Price, Joseph and Justin Wolfers. 2007. "Racial Discrimination Among NBA Referees." *NBER Working Paper* No. 13206.

Ridgeway, Greg. 2006. "Assessing the Effect of Race Bias in Post-traffic Stop Outcomes Using Propensity Scores." *Journal of Quantitative Criminology*, 22(1): 1-29.

Riley, Jack and Greg Ridgeway. 2004. "Commentary: Measuring Racial Profiling by Police." *Law Enforcement News*, June issue,.

Rowe, Brian. 2009. "Gender Bias in the Enforcement of Traffic Laws: Evidence based on a New Empirical Test." Mimeo, Department of Economics, University of Michigan.

Tajfel, Henri and John Turner. 1979. "An Integrative Theory of Intergroup Conflict." In W.G. Austin and S. Worchel (Eds.), *The Social Psychology of Intergroup Relations*, Monterey, CA: Brooks/Cole.

The Alpert Group. 2004. *Miami-Dade Police Department Racial Profiling Study.* (http://www.aclufl.org/issues/racial_justice/miamidaderacialprofilingreport.cfm)

A Misclassification Bias

As we explained earlier in the paper, our proxy variable classifies those motorists who actually traveled exactly at 10 as those who received speed discounting. For the true variable for speed discounting, $1(S < S^*)$, we use $1(S = 10)$ as the proxy variable, given the speed range from 10 to 14. In this Appendix, we follow Hausman, Abrevaya, and Scott-Morton (1998) and correct the misclassification bias. If we assume that once officers decide to give speed discounting, they do not cite a speed level between 11 and 14 (that is, we assume that $\Pr(S < S^*|11 \leq S \leq 14) = 0$), then the misclassification probability is:

$$\alpha = \Pr(S = S^*|S = 10). \tag{A.1}$$

The expected value of the observed proxy variable is

$$E(1(S = 10)|10 \leq S \leq 14,\ X) = \alpha + (1 - \alpha)\Phi(X\beta). \tag{A.2}$$

We can estimate α and β using maximum likelihood estimation under the normality assumption. We found that the misclassification probability is about 0.13, and is significant at the 1% significance level. The estimates β are, however, similar to our previous results. The marginal effect of the interaction term between minority officers and minority motorists is estimated as -0.174, which is also significant at the 1% significance level. The other racial interaction terms turn out to be insignificant.

Figure 1. Histogram of Speeds on Tickets

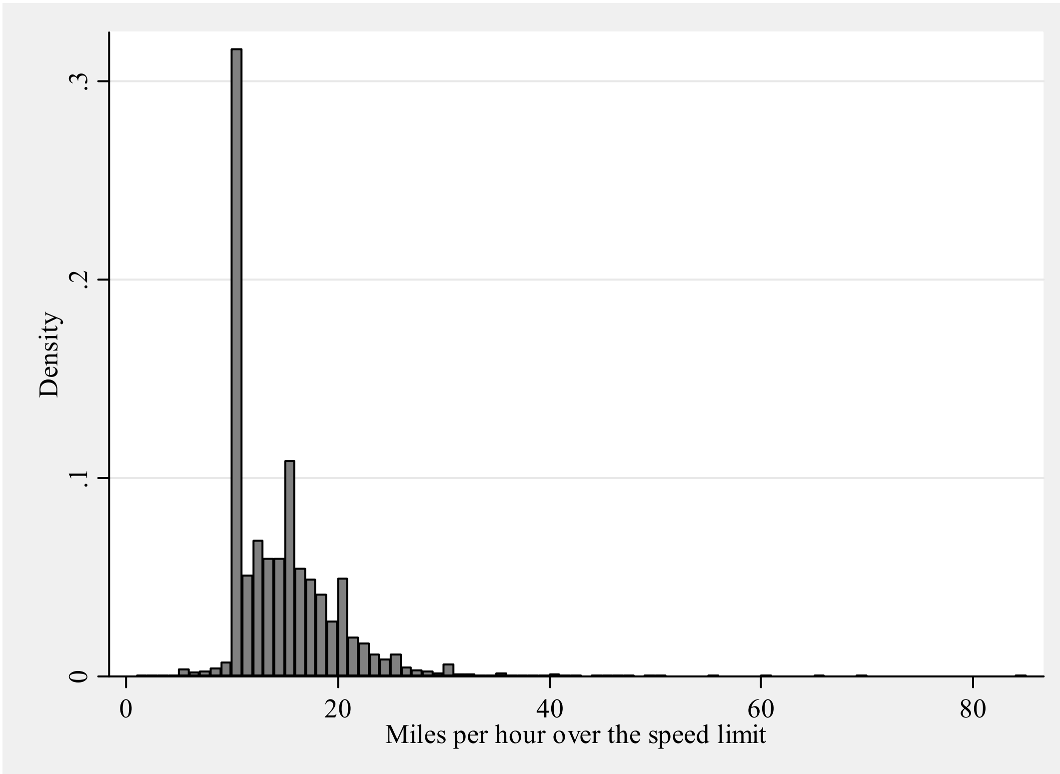


Table 1. Descriptive Statistics of Speeding Tickets

	(1)	(2)	(3)	(4)	Two-Sample Mean Equality Test	
Speed Range	10-14	Exactly 10	Exactly 11	11-14	(2) = (3)	(2) = (4)
Motorist Characteristics						
Age	36.37	36.80	36.02	35.79	$p < 0.01$	$p < 0.01$
	(12.37)	(12.49)	(11.94)	(12.19)		
In Town	0.489	0.454	0.558	0.534	$p < 0.01$	$p < 0.01$
	(0.500)	(0.498)	(0.497)	(0.499)		
In State	0.939	0.936	0.947	0.942	$p = 0.12$	$p = 0.13$
	(0.240)	(0.245)	(0.224)	(0.233)		
Commercial Driver License	0.023	0.023	0.021	0.023	$p = 0.63$	$p = 0.91$
	(0.150)	(0.149)	(0.142)	(0.150)		
Number of Violations	1.330	1.325	1.323	1.336	$p = 0.90$	$p = 0.26$
	(0.548)	(0.549)	(0.523)	(0.547)		
Male	0.645	0.650	0.594	0.638	$p < 0.01$	$p = 0.14$
	(0.479)	(0.477)	(0.491)	(0.481)		
African-American	0.323	0.301	0.377	0.353	$p < 0.01$	$p < 0.01$
	(0.468)	(0.459)	(0.485)	(0.478)		
Hispanic	0.121	0.103	0.146	0.145	$p < 0.01$	$p < 0.01$
	(0.326)	(0.304)	(0.353)	(0.352)		
Officer Characteristics						
Officer Experience	10.61	9.006	13.11	12.74	$p < 0.01$	$p < 0.01$
	(5.382)	(4.434)	(5.734)	(5.776)		
Male	0.975	0.988	0.946	0.957	$p < 0.01$	$p < 0.01$
	(0.157)	(0.109)	(0.227)	(0.203)		
African-American	0.319	0.177	0.628	0.508	$p < 0.01$	$p < 0.01$
	(0.466)	(0.382)	(0.484)	(0.500)		
Hispanic	0.105	0.120	0.073	0.085	$p < 0.01$	$p < 0.01$
	(0.306)	(0.324)	(0.260)	(0.279)		
Environments						
Speed Limit	31.49	31.55	31.63	31.40	$p = 0.62$	$p = 0.06$
	(4.816)	(5.153)	(4.331)	(4.325)		
Morning (6AM–Noon)	0.460	0.535	0.371	0.360	$p < 0.01$	$p < 0.01$
	(0.498)	(0.499)	(0.483)	(0.480)		
Afternoon (Noon–6PM)	0.281	0.251	0.299	0.320	$p < 0.01$	$p < 0.01$
	(0.449)	(0.434)	(0.458)	(0.466)		
Evening (6PM–midnight)	0.206	0.139	0.303	0.295	$p < 0.01$	$p < 0.01$
	(0.404)	(0.346)	(0.460)	(0.456)		
Speed above the Limit	11.09					
	(1.442)					
No. of Observations	14,253	8,130	1,309	6,123		

Notes: Standard deviations are presented in parentheses. Officers' experience is measured in terms of years on the force. The last two columns show the *p*-values for two-sample mean equality tests between the characteristics of tickets cited at 10 and those between 11 and 14. We perform Chi-square tests for dummy variables and t-tests for continuous variables.

Table 2. Difference-in-Difference Estimates: $\Pr(S = 10 \mid 10 \le S \le 14, T = 1)$

	Officers' Race				Differences		
	White (WO)	African-American (AO)	Hispanic (HO)	All Officers	WO–AO	WO–HO	WO–MO
Motorists							
White (WM)	0.706 (4,726)	0.364 (2,182)	0.701 (1,011)	0.611 (7,919)	0.342	0.005	0.235
African-American (AM)	0.690 (2,577)	0.282 (1,693)	0.571 (340)	0.531 (4,610)	0.408		0.363
Hispanic (HM)	0.662 (904)	0.254 (677)	0.483 (143)	0.487 (1,724)		0.179	
All Motorists	0.696 (8,207)	0.317 (4,552)	0.651 (1,494)	0.570 (14,253)			
Differences							
WM–AM	0.016	0.082			–0.066[a] [3.53]		
WM–HM	0.044		0.218			–0.174[b] [3.93]	
WM–MM	0.023	0.151					–0.128[c] [7.96]

Notes: The probability of getting cited at 10 conditional on ticketing, as well as the cited speed being between 10 and 14, is presented. The upper right and lower left panels present the first differences between different groups of officers and motorists, respectively. The lower right panel shows the difference-in-difference (DD) estimates. The numbers of observations for each cell are displayed in parentheses. The absolute value of the *t*-statistic is presented in square brackets. MO stands for minority officers, and MM stands for minority motorists. The three diagonal cells in the right bottom panel are difference-in-difference estimates. [a]: (WM–AM) – (WO–AO). [b]: (WM–HM) – (WO–HO). [c]: (WM–MM) – (WO–MO).

Table 3. Determinants for Speed Discounting

	(1)	(2)	(3)	(4)	(5)
				Fictitious Proxy Variable	
	Pr(S = 10)	**Pr(S = 10)**	**Pr(S = 10)**	**Pr(S = 11)**	**Pr(S = 12)**
Speed Range	**10-14**	**10-11**	**10-19**	**11-14**	**12-14**
Speed Limit	–0.009***	–0.005***	–0.001*	0.008***	0.005**
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Age	0.000	–0.000	0.001	0.001	–0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
In Town	–0.007	–0.006	0.000	0.016	0.006
	(0.009)	(0.008)	(0.007)	(0.012)	(0.016)
In State	0.010	–0.002	0.004	0.012	0.031
	(0.016)	(0.013)	(0.013)	(0.022)	(0.030)
Commercial Driver License	–0.004	0.006	0.001	–0.016	0.051
	(0.026)	(0.022)	(0.021)	(0.034)	(0.046)
Male Motorist	0.068	0.078	0.068**	–0.025	–0.005
	(0.049)	(0.080)	(0.030)	(0.056)	(0.074)
Male Officer	0.320***	0.227***	0.323***	0.028	0.021
	(0.040)	(0.066)	(0.024)	(0.047)	(0.061)
Male Motorist ×	–0.079	–0.064	–0.089***	–0.013	–0.004
Male Officer	(0.049)	(0.080)	(0.031)	(0.057)	(0.075)
Years on the Force	–0.022***	–0.012***	–0.020***	–0.000	–0.003*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
African-American Motorist	0.031	0.026	0.009	0.029	0.059
	(0.026)	(0.034)	(0.019)	(0.033)	(0.046)
Hispanic Motorist	–0.009	–0.012	–0.026	0.036	0.038
	(0.031)	(0.031)	(0.025)	(0.039)	(0.053)
African-American Officer	–0.122***	–0.197***	–0.053**	0.128***	0.131**
	(0.033)	(0.030)	(0.027)	(0.044)	(0.059)
Hispanic Officer	–0.079***	–0.049	–0.082***	0.027	–0.023
	(0.030)	(0.030)	(0.025)	(0.040)	(0.053)
Racial Mismatch	0.012	0.022	0.019	–0.024	0.044
Officer Race ≠ Motorist Race	(0.026)	(0.029)	(0.020)	(0.031)	(0.041)

Minority Motorist × Minority Officer	–0.145*** (0.039)	–0.084** (0.041)	–0.099*** (0.031)	0.010 (0.051)	0.004 (0.070)
African-American Motorist × White Officer	–0.011 (0.031)	–0.030 (0.031)	–0.010 (0.025)	0.024 (0.040)	–0.082 (0.054)
White Motorist × African-American Officer	–0.079** (0.031)	–0.000 (0.033)	–0.081*** (0.025)	0.035 (0.040)	–0.021 (0.054)
# Violations	–0.035*** (0.008)	–0.012* (0.006)	–0.033*** (0.006)	0.014 (0.010)	0.010 (0.013)
Morning	–0.215*** (0.016)	–0.093*** (0.011)	–0.110*** (0.015)	0.019 (0.034)	0.092** (0.043)
Afternoon	–0.246*** (0.016)	–0.091*** (0.012)	–0.176*** (0.015)	–0.024 (0.034)	0.139*** (0.043)
Evening	–0.274*** (0.017)	–0.111*** (0.014)	–0.200*** (0.016)	–0.013 (0.035)	0.102** (0.043)
Day of the Week	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Neighborhood	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Number of Observations	14,253	9,439	21,481	6,123	4,814
R-squared	0.202	0.178	0.153	0.038	0.034

Notes: Estimates from linear probability models. Robust standard errors are in parentheses; and * indicates significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level. Also included are a constant term, six dummy variables for Day of the Week, and 10 dummy variables for Neighborhood.

Table 4. Speed Discounting Conditional on Ticketing: Selection Model

Dependent Variable	(1) **Selection** $1(T = 1)$	(2) **Speed Discounting** $1(S = 10 \mid T = 1)$
Speed Limit	–0.141*** (0.020)	–0.008** (0.004)
Speed Limit Squared	0.002*** (0.000)	
Age	0.010*** (0.003)	0.000 (0.001)
Age Squared	–0.000*** (0.000)	
In Town	–0.044** (0.018)	–0.000 (0.030)
In State	–0.039 (0.029)	0.129*** (0.049)
Commercial Driver License	–0.168*** (0.047)	
Male Motorist	0.095 (0.128)	0.115 (0.117)
Male Officer	–0.137 (0.106)	0.305*** (0.100)
Male Motorist × Male Officer	–0.076 (0.129)	–0.151 (0.119)
Years on the Force	0.008*** (0.002)	–0.014*** (0.004)
African-American Motorist	–0.206*** (0.064)	0.199** (0.098)
Hispanic Motorist	–0.165** (0.076)	0.176 (0.113)
African-American Officer	0.047 (0.071)	–0.131 (0.099)

Hispanic Officer	0.100 (0.075)	–0.011 (0.101)
Racial Mismatch	0.130** (0.066)	–0.066 (0.085)
Minority Motorist × Minority Officer	0.245*** (0.091)	–0.312** (0.129)
African-American Motorist × White Officer	0.082 (0.076)	0.005 (0.113)
White Motorist × African-American Officer	–0.043 (0.076)	0.034 (0.099)
Morning	0.135*** (0.035)	–0.277*** (0.055)
Afternoon	0.093** (0.036)	–0.213*** (0.056)
Evening	0.071* (0.040)	–0.257*** (0.060)
Rho		–0.244** (0.114)
Day of the Week	*Yes*	*Yes*
Neighborhood	*Yes*	*Yes*
Number of Observations =	3,076	1,285
R Squared	0.234	--

Notes: Robust standard errors are in parentheses; * indicates significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level. Column (1) shows the OLS estimates for the selection equation in which the dependent variable is one when a ticket is issued and zero when a warning is issued. Column (2) shows the estimates for the primary equation of the Heckman selection model, where the selection model is specified as Probit. The sample is restricted to April and May, 2001, because warnings were recorded only for those two months.

Table 5. Results for Minority Officers and Minority Motorists across Subsamples

	Subsample 1		Subsample 2	
Officers' Gender	Male Officers	–0.140*** (0.039) [13,896]	Female Officers	-- [357]
Years on the Force	Less than 5 Years	–0.304* (0.167) [1,391]	5 Years and over	–0.090** (0.040) [12,861]
Officers by Total Number of Tickets Issued in 20 Months	Less than 100	–0.201*** (0.070) [4,465]	100 and more	–0.103** (0.049) [9,788]
Motorists' Gender	Male Motorists	–0.176*** (0.048) [9,190]	Female Motorists	–0.091 (0.067) [5,063]
Day and Night	Day 6:00AM –6:00PM	–0.106** (0.048) [10,549]	Night 6:00PM –6:00AM	–0.333*** (0.069) [3,704]
Vehicle Age	Less than 5 Years	-0.011 (0.070) [4,767]	5 Years and over	–0.160** (0.068) [4,475]
Neighborhoods	White	-0.057 (0.050) [9,988]	Minority	-0.280*** (0.085) [3,182]

Notes: The basic model in Table 3 Column (1) is estimated for various subsamples. Robust standard errors are in parentheses; * indicates significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level. All control variables in the basic model are included. The number of observations in each subsample is presented in square brackets. As is explained in the text, we define neighborhoods with 60% or more white population as "white neighborhoods" and those with 20% or more African-American or 20% or more Hispanic population as "minority neighborhoods." We cannot estimate the model separately for female officers because of the small sample size.

Table 6. Further Robustness Checks

	(1) **Controlling for Motorist Home Zip Code**	(3) **Citations Not Involving Vehicle Search**	(3) **African-American and Hispanic Motorists, Separately**	(4) **Excluding African-American Motorists and Officers**
MM × MO	–0.144*** (0.041)	–0.200*** (0.049)		
AM ×AO			–0.080*** (0.018)	
HM × AO			–0.078*** (0.025)	
AM × HO			–0.146*** (0.032)	
HM × HO			–0.170*** (0.046)	–0.165*** (0.046)
AM*AO = HM*AO			0.954	
AM*AO = AM*HO			0.045	
AM*HO = HM*HO			0.654	
HM*AO = HM*HO			0.052	
N =	11,281	13,486	14,253	6,784
R-squared	0.259	0.221	0.202	0.107

Notes: Robust standard errors are in parentheses; * indicates significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level. All control variables in our basic model are also included. The specification is the same as the basic model in Column (1) of Table 3. In Column (3), equalities between coefficient estimates are tested, and the *p*-values are presented.

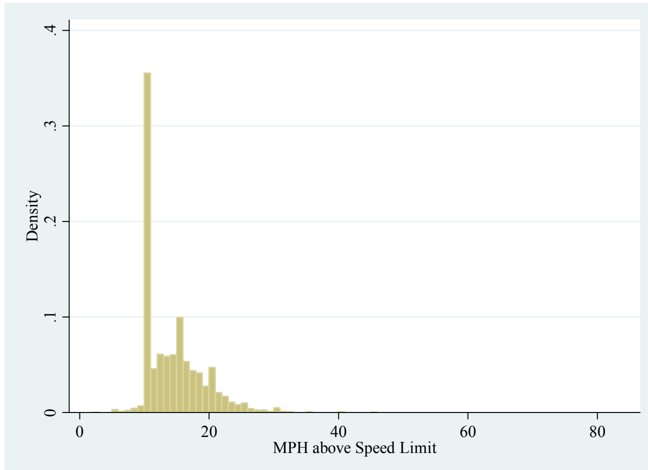
Table 7. Total Number of Citations per Day

	(1)	(2)	(3)	(4)
Dependent Variables	**# Tickets**	**# Citations**	**# Tickets**	**# Tickets**
Sample	**All**	**First Two Months**	**White Neighborhood**	**Minority Neighborhood**
Number of Officers	1.452***	1.695***	1.543***	1.353***
	(0.008)	(0.026)	(0.011)	(0.011)
African-American Officers	–0.075**	–0.061	–0.073	–0.080**
	(0.034)	(0.141)	(0.056)	(0.033)
Hispanic Officers	–0.140***	–0.222*	–0.199***	–0.076***
	(0.030)	(0.123)	(0.049)	(0.029)
African-American Motorists	–0.436***	–0.662***	–0.597***	–0.287***
	(0.034)	(0.140)	(0.056)	(0.033)
Hispanic Motorists	–0.546***	–0.963***	–0.761***	–0.303***
	(0.029)	(0.121)	(0.048)	(0.029)
Racial Mismatch	–0.088***	–0.256***	–0.147***	0.004
	(0.017)	(0.070)	(0.028)	(0.016)
Minority Officers × Minority Motorists	0.330***	0.458***	0.469***	0.178***
	(0.042)	(0.171)	(0.068)	(0.040)
White Officers × African-American Motorists	0.119***	0.225*	0.107**	0.144***
	(0.029)	(0.121)	(0.048)	(0.029)
African-American Officers × White Motorists	0.056*	0.116	0.157***	–0.064**
	(0.029)	(0.121)	(0.048)	(0.029)
Constant	0.278***	0.519***	0.384***	0.205***
	(0.025)	(0.103)	(0.035)	(0.020)
Neighborhood FE	*Yes*	*Yes*	*Yes*	*Yes*
Calendar Day FE	*Yes*	*Yes*	*Yes*	*Yes*
Number of Observations	59,895	9,108	32,670	21,780
R-squared	0.490	0.458	0.501	0.503

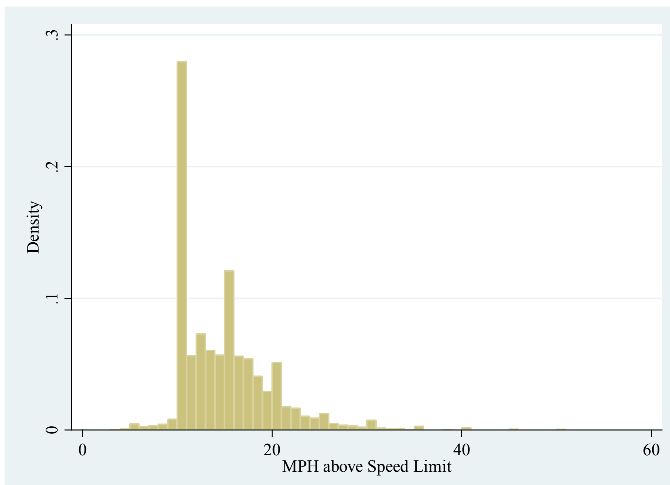
Notes: Robust standard errors are in parentheses; * indicates significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level. There are 605 calendar days, 9 racial matching pairs, and 11 neighborhoods. The maximum number of observations is 59,895 (= 605*9*11). As is explained in the text, we define neighborhoods with 60% or more white population as "white neighborhoods" and those with 20% or more African-American or 20% or more Hispanic population as "minority neighborhoods."

Appendix Figure 1. Histogram of Speeds on Tickets by Driver Race

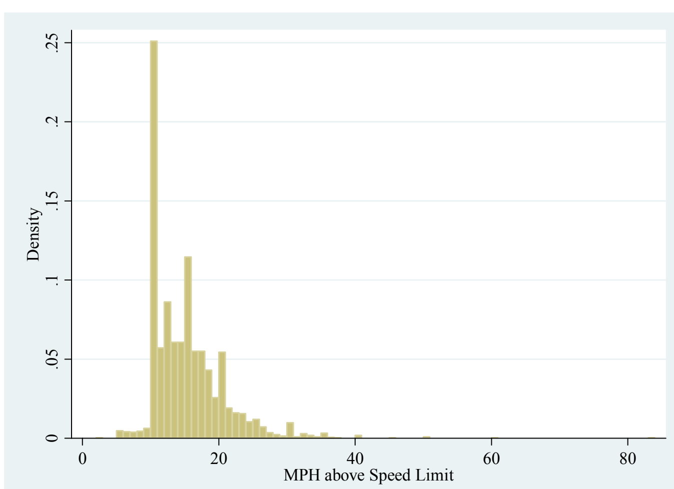
A. White (N = 13,632)



B. African-American Drivers (N = 8,764)

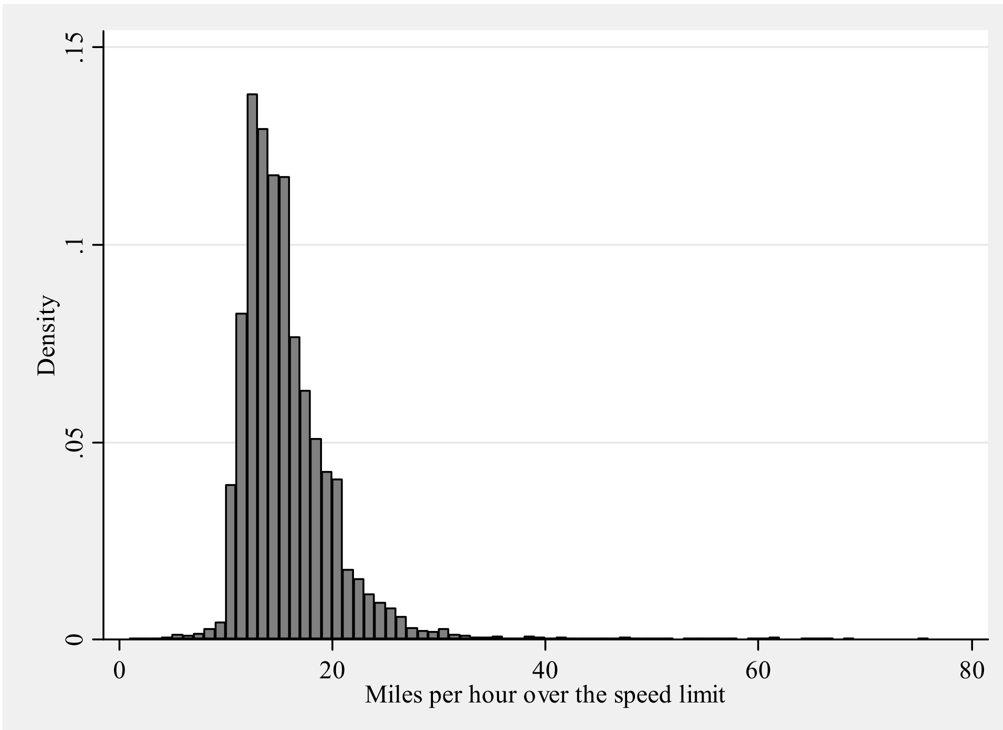


C. Hispanic Drivers (N = 3,342)



Appendix Figure 2. Histogram of Speeds on Tickets

(12,116 Tickets in the City of **Bloomington, IL**, from January 2004 to December 2007)



Notes: The distribution of reported speeds for speeding tickets issued in the City of Bloomington in Illinois between 2004 and 2007. The speeding fines are $75 for up to 20 m.p.h. above the limit, and then increase to $95 for up to 30. In addition, some driving points will be accumulated according to the Illinois point system: 5 points for up to 10, 15 points for up to 14, and so on.