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Man vs. Machine: An Investigation of Speeding Ticket Disparities Based on Gender and Race

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Abstract

This paper analyzes the extent to which police behavior in giving speeding tickets differs from that of automated cameras, which provide an estimate of the population of speeders. In contrast to the automated cameras, the probability of a ticketed driver being African-American or female is significantly higher when the ticket is given by a police officer. This implies that police consider gender and race when issuing speeding tickets. Potential behavioral reasons of this outcome are discussed. The validity of using automated cameras as a population measure for police-issued tickets is thoroughly investigated and supportive evidence is provided.

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I. Introduction

Since the seminal work of Becker (1957), which created the theoretical foundation of the economics of discrimination, researchers have empirically investigated the existence of discrimination in a variety of settings ranging from wages to murder trials.[3] A recent line of research along these dimensions is the investigation of racial and gender bias in motor vehicle searches and ticketing for driving violations. This research explores differential treatment by police officers, which is costly to innocent individuals of a targeted race or gender (Durlauf 2006). Some researchers find evidence of racial or gender discrimination (Antonovics and Knight 2009, Blalock et al. 2007, Makowsky and Stratmann 2009), while others report evidence of no discriminatory behavior by law enforcement officers (Knowles et al. 2001, Persico and Todd 2007, Grogger and Ridgeway 2006).

This paper exploits data from automated speed detection to measure differences in the proportion of speeding tickets issued to gender and racial groups in Lafayette, Louisiana. Automated cameras should be race and gender neutral, since individuals are ticketed by a machine, based solely on their speed violation. By comparing the proportion of women and African-Americans who receive tickets from police officers to those who receive tickets from an automated source, it is possible to determine if police use gender or race as a determinant in issuing speeding tickets. I find that police consider gender and race when deciding to ticket speeders. In the majority of specifications both effects are statistically and economically significant. This result holds even when accounting for potential endogeneity of the location of officers and automated devices.

[3] For example, Munnell et al. (1996) control for credit worthiness, labor characteristics, race, gender, age, job history, and neighborhood characteristics in identifying the impact of race on mortgage rejection rates. Argys and Mocan (2004) investigate the impact of race and gender on death row commutation by controlling for characteristics of the criminal and crime, as well as the governor's party affiliation, race, and gender.

Police may be disproportionately issuing speeding tickets to women and African-Americans due to preference-based discrimination, or because of statistical discrimination. If police enjoy issuing tickets to women and/or African-Americans, they derive an additional non-monetary benefit by ticketing these individuals, which is considered preference-based discrimination. Evidence of the existence of preference-based discrimination is the only way a court will overturn a specific practice by police (Durlauf 2005). Differential treatment based on gender (or race) is considered statistical discrimination if police officers use gender (or race) as a proxy for a relevant characteristic which is difficult to observe. For example, perhaps police frequently ticket women because, on average, they are more likely to pay a speeding ticket fine instead of going to court to contest it (Blalock et al. 2007).

Police officers have a strong incentive to issue tickets which will result in revenues for the city, because the city determines the budget of the police department (Makowsky and Stratmann 2009). If women (African-Americans) are less likely to contest a speeding ticket, it is economically feasible to issue tickets to women (African-Americans), because doing so decreases the chance that the officer will have to go to court. If the officer has to attend court, the marginal cost of issuing that speeding ticket is much higher. Police may also target women or African-Americans if they believe these individuals are more dangerous drivers or are more likely to change their future behavior as a result of a ticket. In the context of this analysis, it is impossible to distinguish between tastes versus revenue maximizing police behavior; however, the first-order issue is whether or not these types of behaviors exist at all.[4] Though taste for discrimination cannot be ruled out, later I present evidence that police behave rationally in that they issue tickets more frequently to drivers speeding more than 15 miles an hour over the limit

[4] In another piece (Quintanar 2011), I test whether police behavior found in this paper is the result of statistical or preference-based discrimination by linking the speeding ticket data to choices made by individuals in dealing with those tickets throughout the court process.

(rather than only traveling 5-14 miles an hour above the speed limit), which is associated with higher fines.[5]

Due to the uniqueness of the data, this paper provides numerous distinct advantages over previous literature. Observing the entire population of speeders is nearly impossible when analyzing the speeding behavior of a whole city, however, automated camera tickets are given to every speeding car that passes in front of the camera. Therefore, the automated tickets provide an entirely objective measure of the speeding population in a given location, which has not previously been used in this type of analysis. Also, in contrast to past research, the present dataset was not collected as a result of a lawsuit.[6] Post-lawsuit data are problematic because police are aware of data collection, as well as its purpose, and may change their behavior to avoid punishment (Grogger and Ridgeway 2006, Blalock et al. 2007, Knowles et al. 2001, Persico and Todd 2007, and Makowsky and Stratmann 2009).

II. Existing Literature

One major issue facing researchers is to find an appropriate measure of the population of offenders to compare to the group who are ticketed, searched, or stopped by police. Grogger and Ridgeway (2006) are able to estimate the population at risk of being stopped by police by using the concept of a "veil of darkness." During the daytime, as opposed to nighttime, it is possible that police use the race of a driver as a determinant of whether or not to stop a car since the driver is visible. Using this rationale, if the race distribution of drivers stopped in darkness, with no visibility, is different than the distribution stopped during daylight; this would be evidence that police engage in racial profiling. Grogger and Ridgeway (2006) exploit information from

[5] Makowsky and Stratmann (2009) report a similar finding: police are more likely to issue a ticket to a driver who was travelling at a faster speed.

[6] Lafayette, Louisiana has no history of legal action taken against the police department for suspected racial or gender based discrimination.

daylight savings time to control for driving patterns, and do not find significant evidence of racial profiling in Oakland, California. Section VI uses a similar methodology to examine the validity of using automated cameras as the population measure for police-issued tickets.

Many researchers utilize stop and search data, where police report drivers who are stopped, the population measure, as well as those who are stopped and subsequently searched. Knowles, Persico, and Todd (2001) find equal success rates for drug searches of motor vehicles driven by blacks and whites in Maryland, thus implying that police engage in statistical, not preference-based discrimination. However, Antonovics and Knight (2009) expand upon the methodology of Knowles et al. (2001) and provide evidence that preference-based discrimination is the more likely explanation for racial disparity in motor vehicle searches since the officer's race impacts likelihood of being searched.

Similarly, findings regarding gender discrimination are inconclusive. Blalock et al. (2007) find that in the majority of locations women were more likely to receive speeding or vehicle maintenance (non-working headlights, etc.) tickets than men.[7] Persico and Todd (2007) generalize the application of their own method using motor vehicle stop and search data, and find no gender discrimination by police.[8] However, Makowsky and Stratman (2009) find females are less likely to receive a fine than males.

In most of the existing literature on this topic, analyses are based necessarily on post-lawsuit data (Grogger and Ridgeway 2006, Blalock et al. 2007, Knowles et al. 2001, Persico and Todd 2007, and Makowsky and Stratmann 2009). Data collection on police behavior generally begins as a result of public suspicion of unfair treatment of African-Americans and the ensuing lawsuit filed against the city or police department. If police officers change their behavior in

[7] Blalock et al. (2007) look at five locations.

[8] Persico and Todd (2007) focus mainly on racial discrimination, but also investigate gender discrimination. Again, they find no evidence of racial discrimination.

order to avoid punishment or stigma, the results obtained from the analysis of post-behavioral change data will reflect a lower-bound estimate of the extent of racial/gender profiling. The dataset used in this paper has a distinct advantage because it was collected without prior knowledge of the Lafayette police department and similarly, the department has no history of legal action regarding discrimination or racial profiling. Also, the automated camera system being used in Lafayette was installed to improve traffic safety, with no consideration of other types of crime reduction or investigation of negative police behavior.

Another common issue in the literature on traffic stops is nonreporting (Grogger and Ridgeway 2006, Knowles et al. 2001, Persico and Todd 2007, Makowsky and Stratmann 2009), which occurs when police officers are asked to record stops and tickets issued, but fail to report all of them. Nonreporting is a problem for studies which investigate behaviors conditional upon being stopped (likelihood of being issued a speeding ticket, given that you are stopped by the police, for example) because the population is not being measured accurately. Audit studies have found a large discrepancy between actual stops and reported stops, especially in initial data collection, where up to 70% of stops were not recorded (Grogger and Ridgeway 2006). The nonreporting problem is not an issue in the present paper, because the dataset utilized herein includes the universe of all issued tickets and the results are not conditional upon being stopped.

III. Data Source and Descriptive Statistics

Lafayette began implementing automated speed cameras in October 2007, with the help of Redflex, the company that created and helps to run these programs across the U.S. and Australia. The dataset is compiled of speeding tickets given by the automated cameras and all speeding tickets given by the Lafayette Police Department. Specific details of the data and how they were collected are discussed below.

1. The City of Lafayette

Lafayette is a city in southern Louisiana with a population of 133,985, about 60 miles west of Baton Rouge (Census 2000). About 65% of Lafayette residents are white and about 30% African-American. Lafayette encompasses five zip codes, 70501, 70503, 70506, 70507, and 70508. Each of these areas has quite different characteristics. Specifically, 69.2% of 70501 residents are African-American, as opposed to 70503 and 70508, where less than 10% of residents are African-American (Census 2000). The gender composition throughout the city does not vary significantly between zip codes, ranging from 47.5% male to 48.8% male (Census 2000). However, income disparity seems to follow a similar pattern as the city's racial composition. Per capita income in the northern area of the city, where there are many more African-American residents, is the lowest, at $12,873, while in the other areas it is higher than $25,000 (Census 2000). Since the socio-economic characteristics of some of Lafayette's zip codes are drastically different, and some are very similar, throughout the remaining paper these zip codes are grouped as follows: 70501 and 70507 compose Area 1, 70503 and 70508 comprise Area 2, and 70506 is Area 3.

2. Police Issued Tickets

The Lafayette City Court database contains every misdemeanor ticket given by an officer in the Lafayette police department within the city limits.[9] The database includes information on the ticketed individual, the badge and name of the police officer who wrote the ticket, time, place, legal speed limit, and speed traveled. Name, gender, age, and home address are taken from the license of the driver, but race is not printed on Louisiana licenses. Officers must individually determine the race of the driver, and this information is provided in the dataset. The

[9] All tickets coded as speeding tickets (86-violation number) as well as speeding tickets reduced to a lesser charge are included in the Lafayette City Court computer database and in the present dataset. Tickets given by State Troopers in the city limits are not in this database.

interpretation by the officer is reliable because officers generally ask each speeder about their race. Also, for those drivers with multiple offenses, the personal information about the speeder is cross-checked when entered into the database.

The majority of officers in the Police Department are white males. Even more strikingly, less than 3% of tickets in the sample are given by officers who are non-white males. Due to the lack of variation in officer characteristics, it is not useful to control for the officer's race or gender.

Police officers use discretion in issuing speeding tickets, but Lafayette City Court sets fines. This is vital, especially in reference to existing research where police motives in issuing tickets may also affect the fine amounts (Makowsky and Stratman 2009). Therefore, differences in fines are not relevant in police behavior.

3. Automated Tickets

Lafayette Consolidated Government, and not the police department, decided to implement the Redflex program and oversee its technology in an attempt to improve traffic safety.[10] The speed cameras are available in two forms: a fixed camera at traffic lights to catch both speeders and vehicles that run red lights, and in "speed vans" which park at different locations throughout the city. The program was implemented in October 2007 with two speed vans giving citations at about 35 different locations.

Though the automated ticketing system continues today, the sample period used in this paper extends from October 2007 to February 2008. During this time, the speed vans gave citations at 64 different locations. The Department of Traffic and Transportation, a department within Lafayette Consolidated Government, determined acceptable locations from accident

[10] The police department did not take control of the program until months after the sample period considered for this analysis.

statistics and individual requests for vans to be placed in specific areas with a speeding problem. Once the requested locations were verified to be safe for a van location, they were added to the list, and continue to be added and removed over the entire sample period. On a particular day and at specific times, the vans are told to locate at randomly selected locations from the overall list.

In December of 2007, automated cameras were placed at four traffic lights in Lafayette. By February of 2008, there were seven stoplight cameras. These cameras were installed at the intersections with the highest crash ratings, based on an analysis of about 30,000 crashes (Lafayette Consolidated Government). The cameras on both vans and traffic lights are completely automatic, and take photographs of the vehicle and driver whenever they detect a car that is traveling faster than the speed limit.

The Redflex database contains every ticket given by automated traffic light cameras as well as those tickets given by speed vans. A paper ticket is sent to the registered owner of the car, who is assumed to be the photographed driver. Lafayette Consolidated Government officials estimate that about five to ten percent of the time, the person driving is not the car's registered owner. Individuals wrongly issued a ticket can choose to pay or refute the ticket by naming the actual driver of the car, who the ticket will be issued to instead. It is more common for individuals to just pay the ticket instead of arguing, especially instances where a young person was driving a parent's car, etc.[11]

The information available from the automated tickets is: name and home address of the registered owner of the vehicle, location, time and date of the ticket, legal speed limit, and speed

[11]The information in the preceding paragraph was provided through personal communication with Tony Trammel, Director of the Department of Traffic and Transportation. Instances when a ticket was refuted can be observed in the data because a letter is added to the citation number every time the ticket is contested and reassigned. This occurs rarely, in about 7% of the sample.

traveled. There are also four pictures on each ticket, most importantly, two of the driver, from which gender and race can be determined.[12] Since automated tickets are easier to give and require less manpower, they are issued much more frequently than police tickets. During the sample period the average number of automated tickets was 3,100 per month.

4. Data

The sample includes every speeding ticket issued between 6:00 A.M. and 6:59 P.M. from October 2007 to February 2008. The police portion of the data includes every ticket issued by a Lafayette city police officer within the city limits. Since the number of automated tickets had to be handled record by record, and each individual's characteristics had to be manually determined, a 15% random sample was chosen from the population of automated tickets. Because of low visibility of individual drivers at night, only daytime tickets are used in the main analysis so that race and gender can be identified. In a later analysis, a longer time period of police-issued tickets are utilized, to take advantage of differences in visibility in a similar manner to Grogger and Ridgeway (2006).

Table 1 lists descriptive statistics of all ticket data. About 26% of ticketed drivers are African-American and 46% are female. Half of the tickets are given in Area 1, the area with a higher proportion of African-American residents. The average ticketed driver was traveling about 51 miles an hour, with 79% of ticketed drivers speeding between 5 and 15 miles over the legal limit.

To provide a sense of the differences between tickets given by police and the automated system, Table 2 lists descriptive statistics broken down by area and source of ticket. Police issue a significantly higher proportion of speeding tickets to African-Americans than the automated

[12] One is a close up of the driver's seat, while the other is taken from a further distance and has the entire front of the car in view.

sources in Area 1. In the other areas, police issue the same proportion of speeding tickets to African-Americans as the automated sources. However, there is an obvious difference in the proportion of tickets issued to women by automated cameras compared to police officers. In Areas 1 and 3 this difference is statistically significant; where police give 51% and 58% of tickets to women, respectively, but automated sources give about 40% in both areas.

5. Motivation for Police Behavior

Merely because police issue a disproportionate amount of tickets to women and African-Americans does not mean that they are engaging in discriminatory behavior. Perhaps there is another difference in how tickets are issued, such as the cost of issuing tickets. The automated cameras can easily issue tickets to every car that passes, but police must spend time to issue a ticket, and while issuing tickets they must let other speeders pass unpunished.

Table 2 illustrates this more clearly by looking at the means of the speed-related variables. For instance, the variables which measure how fast an individual was traveling illustrate an important difference between the automatically issued tickets and police tickets: the majority of automated tickets are issued at lower severities of speeding.[13] Conversely, most police issued tickets are given in the *16-20 Miles Over* range. Merely 8% of all police issued tickets are given to motor vehicles traveling only 5-10 miles above the speed limit. Police stop and ticket individuals who are traveling at higher speeds because the cost of stopping speeders is the same regardless of speed, but the marginal benefit is greater for more severe offenders. Individuals who receive tickets for higher speeds must pay a higher fine,[14] which results in

[13] Though, note that neither police officers nor the automated system issue tickets to speeders traveling 5 miles or less over the speed limit.

[14] Lafayette City Court bases fines on the severity of the speeding violation, however, individuals who have received prior traffic violations or committed the violation in a school or construction zone will have higher fines all else equal.

higher revenues for the City of Lafayette, and in turn, likely a higher budget for the police department (Makowsky and Stratmann 2009).

Figures 1 and 2 further illustrate the different ticket issuing behavior of police and automated sources. In Figure 1, the tendency for police officers to ticket higher speeders is easily observable, as the majority of tickets seem to be issued between 13 and 17 miles over the limit. Tickets issued for speeders traveling between 15 and 17 miles over the limit are associated with significantly higher fines than tickets issued for violations of 5 to 14 miles over the limit, which may provide an incentive for officers to focus on more extreme speeders. Some may argue that police officers ticket higher speeders because they are more dangerous, however, there is unlikely to be a difference in the level of danger between speeders traveling 14 miles over the limit and 15. Despite this fact, the number of tickets issued by police to speeders jumps as the speeding severity crosses the 15 miles per hour threshold. Along these lines, Garrett and Wagner (2009) use annual data from North Carolina counties to show that police issue significantly more tickets in years following a decline in revenue, which also illustrates the importance of fiscal concerns when issuing tickets.

Figure 2 illustrates the relative frequency of speeding tickets issued by speed over the limit for the automated cameras (speed vans and traffic lights). In Figure 2, the majority of tickets are issued to drivers traveling between 8 and 10 miles over the limit. This difference in police officer behavior from the automated ticket “behavior” implies that police use different criteria when issuing speeding tickets than automated cameras.

When using stop and search data, police may use race as a proxy for carrying drugs or weapons and thus use a violation as the official reason to stop a car, but in reality are interested in searching the vehicle for said contraband. If this type of statistical discrimination exists in issuing speeding tickets, more African-Americans will receive speeding issued tickets, though not as a result of racial bias. In Lafayette, police consider speeding a serious offense in and of itself, and assume that vehicle maintenance issues are more strongly correlated with likelihood to carry illegal substances or weapons. Police are less likely to use speeding as a reason to pull over and search a vehicle than they are to use visible vehicle maintenance issues, specifically in high crime areas. Furthermore, drug crimes and gun violence are not a critical concern for the city of Lafayette, so this type of statistical discrimination should not play a major role in stops within the city.[15]

One potential data issue that is not present in other literature arises because Lafayette is a relatively small city, where the majority of officers are white males. If police officers happen to stop individuals they know personally (e.g. another white male), and let them go without a ticket, the results may create an impression of race or gender bias when it is actually a result of corruption, based on personal relationships. Even if this was the case, the effect should be minor since the city is large enough that police officers do not know everyone. Also, the magnitude of the results here are substantial enough that it is unlikely that they are driven by this type of behavior.

IV. Validity of Automated Tickets as a Population Measure

1. Automated Tickets: Vans and Traffic Light Cameras

As previously discussed, the automated cameras come in two forms: fixed cameras at traffic lights and mobile vans. If drivers behave differently at traffic lights, then using traffic light cameras as a comparable measure of the speeding population will not be accurate. Perhaps individuals are more cautious and slow down when crossing an intersection, while they speed on

[15] The Lafayette Police Department provided the information in the preceding paragraph through personal communication; specific behavior within the city of Lafayette, excluding highways.

other stretches of the same road. Similarly, residents of Lafayette are generally aware of which intersections have a traffic light camera, so it is possible that individuals change their driving behavior in these areas in order to avoid a fine.[16] If women and African-Americans are more risk averse, they may avoid intersections with traffic cameras or may be more cautious by driving slowly in these areas. If this is the case, a lower proportion of automated tickets given to African-Americans and women may reflect this change in behavior, rendering the comparison between police tickets and automated tickets invalid.

Figures 3 and 4 illustrate that drivers do behave differently when driving past a speed van camera and a traffic light camera. While the majority of speed van speeding tickets are issued to individuals driving between 6 and 16 miles over the limit, more than 60% of the traffic light tickets are given to drivers traveling between 8 and 10 miles over the limit.

Functionally, speed vans provide a more accurate comparison to police officers. Speed vans move in a random fashion, making it more difficult for drivers to predict their locations and they are as easy to identify as a police car. Therefore, drivers should behave in the same manner around police cars and speed vans. For the reasons listed above, it seems likely that driver behavior around speed vans is more similar to their behavior around police officers than their behavior at intersections with traffic light cameras.

2. Automated versus Police-Issued

In order for the automated issued tickets to provide a valid comparison group to police issued tickets, both ticketing sources must measure the same driving (speeding) population. Police observe the population of speeders, but are only able to ticket a select number, while the automated cameras ticket the entire population of speeders objectively. If police do not observe

[16] As in Bar-Ilan and Sacerdote (2004), where they find individuals do alter behavior in order to avoid an increase in a fine for running a red light. It is not hard to imagine this same behavior in order to avoid a speeding ticket.

the same population, any difference in ticketing may be the result of the different population of speeders and not a difference in ticketing behavior. While there are some procedural differences that need to be considered, the descriptive evidence below suggests that the populations being measured are comparable. In Section VIII, I more explicitly account for potential endogeneity with propensity score matching and exploitation of police visibility using daylight savings time.

The first step to show the equivalence of the police-observed population and the automated-observed population is to understand the exogenous locating procedures used for both ticketing sources. If police have the freedom to patrol where they please, they may choose to target areas where certain groups travel. For example, if police have a preference for ticketing African-Americans, and locate where more African-Americans travel, more African-Americans will receive tickets. If the automated tickets are not given in those specific areas, the amount of tickets issued to African-Americans by police would be higher in comparison to automated tickets in other areas, but this would reflect the differential exposure rates, not police discrimination.[17]

In the case of tickets issued by police, the data only specify the location of the violation, but not how or why the officer was located there. There are two different types of police officers who issue speeding tickets; traffic officers and patrol officers. Traffic officers are sent to specifically target speeders and other traffic offenders, while patrol officers can be sent for these

[17] Another scenario may initially seem plausible as well, motivated by the difference in means of speed limit by ticketing type, as seen in Table 2. Since automated cameras ticket on streets with a higher average speed limit than police, perhaps these automated cameras are being placed on busier roads used for commuting, while police are locating in neighborhoods and school areas, where there are other safety concerns besides speeding. If this is the case, and women and African-Americans are more likely to travel in neighborhoods, while men and whites are more likely to travel on the busy commuting routes, then the results herein are being driven by this fact and not police discrimination. This scenario cannot be the driving force of these results however, because the neighborhoods and school zones where police are locating are public schools with a majority of white students, and white neighborhoods. Therefore, if different ticketing populations were the true source of the differential ticketing, whites would receive more tickets from police than automated sources, the opposite of the present findings. Though there is not as simple of an explanation regarding gender, it is unlikely that this type of selection could be driving the entire result.

or more general reasons. Both types of officers are assigned to certain areas in Lafayette for each shift, and thus should not be differentially locating based on gender or race of individuals.[18] Even if only traffic officers' tickets are used, there is no difference in results.

Although the mobile automated cameras are randomly assigned to a location during the day, the locations themselves are not completely random. First, only areas where it is safe to place a van will be placed on the master list. In this context, "safe" is used only in reference to van parking; streets with no shoulder or sidewalk may be considered "unsafe" because there is a significant risk of danger from passing traffic merely by parking there.[19] However, this should not be a major issue. Redflex states that its mobile cameras can be used, "on suburban streets, as well as on higher-speed thoroughfares, either by parking in a safe position on the roadway or nearby for added safety" (Redflex, 2010). Based on this definition, it is feasible that police will also search for speeders in a "safe" spot, despite the fact that this is not explicitly stated in police procedure.

The other source of non-randomness in speed van locations is that the initial acceptable list includes areas known to have speeding problems; and as such, tend to be busier streets instead of neighborhood roads. Similarly, because the goal of this program is to reduce speeding, the areas that have the most impact on speeders also tend to be busier city streets. This can be seen in Table 2, where the majority of tickets issued by automated sources are issued on streets with relatively high speed limits. Over time, because individuals can request a van be placed in their neighborhood, these neighborhood locations are added to the list, but the number

[18] The Lafayette Police Department provided the information in the preceding paragraph through personal communication.

[19] The important distinction here is that vans or police officers may still choose to locate in high crime areas, if those areas also suffer from speeding drivers.

of tickets issued on busier streets is much larger than the number of tickets issued on streets with lower legal speed limits.

Police also locate on busy streets, but they tend to focus more on ticketing speeders in neighborhoods, particularly near schools. In school zones, the legal speed is much lower than larger city streets. This is one reason why the average speed limit for police issued tickets is less than the mean speed for automated issued tickets. Police locate in neighborhoods, but generally on streets with high traffic volume; streets with low speed limits that are used by a large number of travelers. This does not affect the validity of the comparison, because vans locate in nearly the same areas as well.[20]

The ideal measure of the police-observed speeding population is to use all drivers at the locations where police issue tickets. However, this is not feasible for several reasons. The most obvious of these reasons is that if automated sources and police officers chose to locate at the same locations, they would not be maximizing speed-deterrence. If a police officer is traveling to a designated spot to target speeders, and upon arriving sees a mobile van, he/she will most likely travel to a nearby street, or nearby block. In the sample, as can be seen from Figure 5, there are some instances where an automated van camera and police officer ticketed a speeder in the same location, however, it is more common for tickets to be issued nearby, generally within a block or two. This does not create a bias, because individuals who drive in neighborhoods also must drive on the busier city streets where vans are located nearby.

Figure 5 shows the city of Lafayette, with dots representing the frequency of tickets issued by each ticketing source, at specific locations. Empty dots represent police-issued tickets and the darkest filled dots represent speed van issued tickets. The dots are sized proportionately

[20] When school zones are excluded from the analysis, the police coefficient is actually larger than before.

to the frequency of tickets that were issued at that location.[21] For example, in many instances only one ticket is issued in a location and these dots are the smallest on Figure 5. Similarly, there are relatively few locations where more than 100 tickets are issued during the range of data collection for the sample. This generally occurs when tickets are issued by automated sources, but there are a few police issued locations where this is also true.

The western portion of the map, which includes zip codes 70506 and 70503, illustrates a fairly equal coverage of mobile vans and police officers. This is extremely close to the ideal of having speeding tickets issued by automated sources and police officers in the exact same locations. Since there are automated vans and police officers in near proximity to one another, it is feasible to assume that both ticketing sources are observing the same population of speeders, when controlling for time of day, day of the week, etc.

However, the northern portion of the map, above Interstate 10, is zip code 70507, is not useful in this comparison, because the only source of automated tickets is one traffic light camera at the northern city limit. No speed van tickets were issued here. Because this area of the city has a large number of African-American residents, it is no surprise that speeding tickets issued in this zip code will be issued disproportionately to African-Americans. Since there are no valid comparison automated tickets issued in this area, there is not an accurate measure of the speeding population. Therefore, I exclude this area from the remaining analysis. The exclusion of this area does not impact the validity of the results, because this results in a sample size reduction of only 77 tickets. Similarly, this is a relatively small portion of the overall city with the bulk of the area being residential. The main commercial areas and majority of city neighborhoods are south

[21] Size of the bubbles was determined based on the equation: Size = (Frequency of Tickets Issued / Maximum Frequency of Tickets Issued at One Location).

of Interstate 10. For these reasons, the remaining analysis will not include tickets issued in the zip code of 70507.

Though there is a greater discrepancy between police and automated ticket locations in the remaining zip codes, 70501 and 70508, tickets are still issued within blocks of each other. Vans and police officers issue tickets in the same neighborhoods, or a police officer may issue tickets within a neighborhood while a van issues tickets on a nearby street where those residents must travel to get home. Therefore, automated tickets remain a valid measure of the speeding population.

Figures 6 and 7 provide the same evidence as Figure 5, but they show tickets only where race or gender is observable. These three maps show that police tickets and tickets generated by automated sources are issued in nearly identical locations. The estimation methods and results are discussed in the following sections, but due to the differences between traffic light cameras and police issued tickets, traffic light tickets are not included in the main specifications.[22]

V. Methods

If the racial and gender composition of speeders who are ticketed by police is different than the racial and gender composition of the entire population of speeders, police are treating individuals differently based on gender and/or race. However, observing the entire population of speeders is costly, and nearly impossible when looking at the speeding behavior of a whole city. Alternatively, because the automated tickets are given to every speeding car detected by the camera, automated ticket systems provide a measure of the speeding population in a given location. This technique also provides an advantage over previous literature, where the

[22] When traffic light cameras are included, the results are qualitatively the same and can be provided upon request.

population measures are not completely objective.[23] If police do not consider race or gender when they issue tickets, then the proportion of tickets issued to certain sub-groups of the population (such as females or African-Americans) should not differ between police and vans or light cameras.

I will use individual level tickets to investigate police behavior in issuing speeding tickets. Thus, I address the following empirical question: Given a driver is caught speeding and issued a ticket, is the probability of being black (or female) the same regardless of the ticketing source, that is

$$\Pr(Black|Ticket, Police) = \Pr(Black|Ticket, Automated)?$$

The analysis will be performed at the individual level, with the dependent variable a dummy equal to 1 if the ticketed individual is African-American and 0 otherwise (or female/male). The advantage of the individual-level analysis is that the richness of the data will allow for control of most factors that police may use to decide whether to ticket an individual, such as severity of the speed violation, the speed limit where the ticket was given, as well as other determinants of ticketing, which include the day of the week, and the location of the infraction. The specification is depicted by Equation (1)

$$B_i = \alpha + X_i'\beta + \gamma Pol_i + \varepsilon_i \quad (1)$$

where B_i is equal to 1 if the recipient is black, and zero otherwise (or equal to 1 if the recipient is female and 0 otherwise), X_i includes specific characteristics of the violation, and Pol_i is a dummy variable equal to 1 if the ticket was given by a police officer and 0 if the ticket was given by an automated source. In this specification, if the coefficient of the dummy variable for

[23] For example, Grogger and Ridgeway (2006) use tickets issued at night as a population measure, but police can likely still observe car type, which may be correlated with race. Therefore, this may not be a completely objective measure of the population.

a police-given ticket (γ) is positive and statistically significant, this implies that race (or gender) may play a role in a police officer's decision to pull over and ticket a speeder.

VI. Results

Table 3 shows the results of estimating Equation (1), using only tickets issued by police officers and speed vans. The entries are marginal effects; and robust standard errors, clustered by area, are reported in parentheses. The areas are broken down into their respective zip codes, as previously defined,[24] and each column successively increases the number of zip codes included in estimation. Column I (IV) only includes tickets issued in areas with the greatest overlap of ticket locations for police and speed vans. Column II (V) includes an additional zip code which also contains ticket locations that are very similar, followed by Column III (VI) which includes all zip codes except for 70507, where no automated van tickets are issued. Restricting the area significantly decreases the sample size, but in all specifications the marginal effect for the police dummy variable remains positive and significant. All columns control for area fixed effects, whether the ticket was given in the first half of the month, whether the ticket was issued during morning or evening rush hour, the legal speed limit where the ticket was issued, severity of the speeding violation (*11-15 Miles Over, 16-20 Miles Over*, and *More than 20 Miles Over*), time controls, and day of the week fixed effects.

The police coefficient is positive and significant in the first three columns, where *African-American* is the dependent variable, implying that the probability of being African-American is higher if the ticket was given by a police officer than if it was given by an automated source. In Column III, *Area 1* is positive and statistically significant, as expected, implying that African-Americans receive more tickets and reflecting the fact that Area 1 has a

[24] Area 1 is 70501, Area 2 is 70503 and 70508, and Area 3 is 70506. Recall that Lafayette has an additional zip code, 70507, which is not included due to a lack of adequate ticketing by the automated sources. The fundamental results are the same when police precincts are used as area controls instead of zip codes.

large number of African-American residents. Conversely, there are relatively few African-American residents in Area 2 (less than 10%), and the estimated coefficient for *Area 2* is statistically significant and negative in all specifications. *HalfMonth 1* is added to test conventional wisdom that police ticket differentially depending on the time of month, but is not significant in any specification.

The next control is legal speed limit. As previously discussed, some tickets are given on busy city roads, and others on neighborhood streets, so this control will help to further specify driving patterns. *LegalSpeed* is statistically significant, but is close to zero.

The controls for severity of the violation are a range of dummy variables (*11-15 Miles Over, 16-20 Miles Over, More than 20 Miles Over*) which are equal to one if the violation was within the range and 0 otherwise. These controls are not consistently significant in any specification. Day of the week fixed effects are included to further control for driving patterns. *Saturday* is positive and significant in Columns I and III, though no other day fixed effects are consistently significant.

I use a dummy variable, *RushHour*, to control for travel differences, which is equal to 1 if the ticket is given between 7:00 am and 8:59 am or 5:00 pm and 6:59 pm, and 0 otherwise. The impact of *RushHour* is significant in Columns I and II. In a similar vein, since driving patterns may differ by race or gender based on the time of day the ticket was issued (Grogger and Ridgeway 2006, Blalock et al. 2007), the last controls are hourly controls: *6:00 to 8:59 AM, 9:00 to 11:59 AM, 12:00 to 2:59 PM, 3:00 to 5:59 PM, and 6:00 to 6:59 PM*. The hourly controls are significant, though of differing magnitudes.

Overall, the results using the largest sample area indicate that, all else the same, it is about 8 percentage points more likely that the recipient of a police-given speeding ticket is black, as opposed to the recipient of a speed van issued ticket.

The latter three columns of Table 3 present the results where the dependent variable is a dummy equal to 1 if the violator is female and 0 if the violator is male. The initial probit estimation, where the sample zip codes include 70506 and 70503, estimates the marginal effect of police to be .209, and is statistically significant at a 5% level. The magnitude of this result should be interpreted with caution, due to the relatively small sample. In Columns V and VI, with the larger sample area, the police coefficient remains statistically significant at the 5% level, while its magnitude decreases to .138.[25]

The police coefficient of the model including the larger area indicates that conditional on being issued a ticket, the probability of a speeding ticket being received by a female is about 14 percentage points higher when the ticket was issued by a police officer. Since there are no significant advantages to reducing the sample area, the remaining tables will include tickets issued in 70506, 70503, 70508, and 70501.[26]

Table 4 provides a more rigorous investigation of police behavior, by using only a specific sample of tickets from the population to determine whether gender and racial differences in receiving tickets persist within a specific group. Column I includes only tickets given to

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[25] One concern is that 70506 and 70503 may be driving these results. However, even when these zip codes are excluded, the coefficient on the police dummy is smaller, but still significant (.044 at a 5% level). These zip codes include commercial as well as residential areas, similar to the other zip codes in this analysis, so it is unclear why there would be a difference in ticketing based on gender in the area.

[26] All specifications were also run using police tickets and both sources of automated tickets, results of which can be provided upon request. In general, the police coefficient decreases compared to the specifications which do not include traffic light camera tickets, implying that women and African-Americans actually receive even fewer tickets from speed vans than from both automated sources combined. This could mean that men and whites are more likely to adjust behavior when aware of an automated camera (or that they drive comparably slower through intersections). Using both automated sources does not change the overall finding that the probability of a ticketed speeder being a woman or African-American is higher for tickets issued by police officers, in any specification.

women, with the dependent variable a dummy equal to one if the woman is African-American and 0 otherwise. The police coefficient is positive, but it is no longer significant at conventional levels. Of tickets given to women, police do not seem to ticket differentially based on race. In Column II, only tickets given to males are included, and the police coefficient is positive and statistically significant. This suggests that when ticketing men, police are more likely to ticket African-Americans as compared to automated sources, relative to ticketing whites.

Columns III and IV of Table 4 use a dummy equal to 1 if the violator is female and equal to 0 otherwise as the dependent variable, but restrict the sample based on race. Only those tickets given to African-Americans are used in the regression reported in Column III, and only tickets given to individuals who are not African-American are employed in the regression for Column IV. Column III implies that African-American women are about 9 percentage points more likely to receive a ticket from a police officer as African-American men, compared to the likelihood of receiving a ticket from an automated source. Column IV illustrates that it is more likely for a white individual to be female if the ticket was issued by a police officer.[27] In summary, controlling for gender, a ticketed driver is still more likely to be African-American if ticketed by the police, and controlling for being non-African-American, a ticketed driver is more likely to be female if ticketed by police.

VI. Investigating Econometric Issues of Endogeneity

1. Propensity Score Estimation

As previously mentioned, police and automated cameras do not always ticket in the exact same location. Although the preceding sections begin to justify the use of automated tickets as a comparison group to police issued tickets, this section aims to more explicitly show that the

[27] The comparison group to African-American tickets is actually all other races; however, in Lafayette about 97% of the ticketed population is white or African-American.

previous findings are valid by implementing a propensity score estimator. The underlying issue is one of selection: if police choose to locate in areas that are different than automated sources, the different proportions of tickets issued to African-Americans and women may merely be the result of selection bias. If we think of receiving a ticket from a police officer as the "treatment," where we are interested in the gender and race of the ticketed driver, the propensity score estimator provides a method of comparing similar automated and police ticketed speeders. Specifically, by estimating the propensity score (the likelihood a driver is ticketed by the police based on violation and location characteristics) the selection problem is less severe.[28]

The first step is to estimate the propensity score using a logit model where the dependent variable equals 1 if the ticketed driver was African-American. The propensity score is a function of relevant covariates (area dummies, *11-15 Miles Over the Limit*, *16-20 Miles Over the Limit, More than 21 Miles Over,* day of the week dummies, *9:00 to 11:59 AM, 12:00 to 2:59 PM, 3:00 to 5:59 PM, and 6:00 to 6:59 PM,* and month dummies), where conditional on the propensity score, they are independent of treatment (Mocan and Tekin 2006).

Once the propensity score is estimated, there are numerous methods to estimate a nonparametric regression to determine the average effect of treatment on the treated (ATT). I employ nearest neighbor matching with and without replacement, along with radius caliper matching. First, nearest neighbor matching matches individuals ticketed by police with individuals ticketed by automated sources based on their propensity score; the observations with the closest propensity score are matched. Nearest neighbor matching with replacement means an untreated (automated-issued) individual can be matched multiple times, but nearest neighbor matching without replacement limits the use of an automated ticketed individual as a match only

[28] Notice however, this is not an end-all solution: if there are unobservable individual driver attributes which are correlated with the likelihood to be ticketed by the police as well as correlated with the likelihood that an individual is African-American or a woman, standard problems of biased coefficients remain.

once. Since estimation without replacement may depend on the order of the data (Dehejia and Wahba 2002), I follow convention and order the data randomly, as well as in ascending and descending propensity score order. The results remain consistent, as can be seen in Table 5. The estimates using nearest neighbor matching with replacement are no longer significant for African-Americans, but are still significant when gender is the dependent variable.

Lastly, I employ radius matching, using two different calipers (range of propensity scores). Radius matching uses all automated ticket observations in a specified propensity score range to match police ticketed observations, and the results are overall similar to previous columns. The effect for race loses significance in some specifications, but women consistently are more likely to be ticketed by police officers than automated cameras. This further supports results in previous sections.

2. Utilizing Daylight Savings Time

Next, I explore a slightly different approach, to provide suggestive evidence that the automated cameras are a valid population measure and comparison group to the police-issued cameras. Similar to Grogger and Ridgeway (2006), I restrict the estimation sample to police-issued tickets between 6:00 AM and 7:59 AM, and between 5:00 PM and 6:59 PM. I supplement my dataset with sunrise and sunset data taken from the U.S. Naval Base. As a result of daylight savings time, some tickets are issued in the dark while some are issued in daylight, even though the clock time of the issued ticket is the same. In other words, in November the sun sets around 5:30 PM, but in October the sun sets around 6:30 PM. This means that someone who received a ticket in November at 6:00 PM received a ticket when it was dark outside, and the police officer likely could not see inside the vehicle (and thus, could not determine race or gender of the driver). However, if another driver was ticketed at 6:00 PM in October, when it was light outside, police officers could see inside the vehicle.

Assuming that police officers cannot observe a driver's race or gender when it is dark outside, any difference in issuance to African-Americans or women when it is light as compared to when it is dark implies that police officers do consider race or gender in issuing tickets. Utilizing daylight savings time allows for keeping time of day constant, while providing the ability to compare tickets issued in light to those issued in the dark. A control, *Morning*, is also added in case there are differences in driving patterns during the morning and evening hours (*Morning=1* if the ticket was issued between 6:00 and 7:59 and 0 if it was issued between 5:00 and 6:59). All other controls are the same as previous tables.

The coefficient of interest is *Daylight Visibility*, which equals 1 if it is light outside (if the ticket was issued on that day after the sun rose and before it set), and 0 if it is dark outside (if the ticket was issued on that day before the sun rose or after it set). Table 6 provides means and standard deviations of this new control variable in terms of gender and race, independently as issued by police and automated sources. Since automated cameras are assumed to measure the population of speeders at a given location, regardless of whether it is light or dark outside, we can compare the proportion of these tickets to those issued by police officers, to determine if there is a difference in issuing based on visibility.

Initially, if we compare police and automated issued tickets only issued during daylight hours, when drivers are visible to police, there is an obvious difference in ticketing behavior. Police issue a greater proportion of tickets to African-Americans as well as women, though this raw difference is only significant for gender. These rough results coincide with the earlier findings of this paper. Conversely, during dark hours when there is no visibility, the proportion of tickets issued to women and African-Americans by police and automated sources are very similar. Since this difference only arises when there is visibility of drivers, this implies that police are using some subjective criteria once observing the speeding driver to determine whether or not to issue a ticket.[29] Recall that these estimates include only tickets issued between 6:00 and 7:59 AM and 5:00 and 6:59 PM, and so it is unlikely that these results are driven by differences in driving patterns. Though these statistics are extremely useful for analyzing trends in the raw data, a more thorough approach needs to be used to provide more reliable results.

The regression results including daylight controls are presented in Table 7, which support the previous results and imply that African-Americans and females are more likely to receive a ticket from a police officer only when race or gender is visible. If the same exercise is performed using only automated issued tickets, the coefficient on *Daylight Visibility* is not significant, as can be seen in Table 8. Since automated sources are objective there should be no difference in ticketing by race or gender merely because it is light as opposed to dark.

The coefficient on *Daylight Visibility* is significant only when considering police issued tickets, which coincides with results when automated cameras are used as the comparison to police-issued tickets, providing supportive evidence that the automated cameras can be used as a valid comparison group.

VII. Conclusion

This paper aims to explain whether police issue speeding tickets differently to individuals based on their race or gender. I find that in the city of Lafayette, Louisiana, the probability of a ticketed driver being a woman or African-American is significantly higher if the ticket was issued by a police officer versus an automated source. Since automated sources issue speeding

[29] It has been discussed that police may still infer gender or race based on the car model, type, or even color. Therefore, police may still be able to consider these factors, though at a lesser influence.

tickets to every speeding car that passes, this implies that gender and race play a role when police decide whether to ticket a speeding driver. Even when controlling for additional factors like severity of the speeding violation, time of day, actual speed limit, and day of the week, the results remain the same.

This methodology has not been used previously to study police behavior and differential treatment in receiving speeding tickets based on gender and race.[30] As a result of the specific type of analysis, this paper does not suffer from common issues in this realm of literature. The city implemented the automated camera system to improve safety and decrease the number of crashes caused by red light runners, and was not intended for any use involving investigation of police bias. Also, these data were not collected as a result of a lawsuit, and therefore police had no incentive to alter their behavior. Similarly, the present dataset includes all speeding tickets given during the sample time period and does not rely on police reports. Every instance when a police officer wrote a ticket is included and police cannot misreport their actions.

This paper also has a large advantage over existing literature because it employs a completely objective measure of the speeding population. For the most part, vans and police officers are located either very close to each other (on the same street or city block), or they are within a few blocks of each other. This suggests that police officers and vans are not differentially located to deliberately target different sub-populations. This provides a distinct advantage in that after controlling for incident and street characteristics, any differences between automated and police issued tickets arise from the subjective nature of police tickets.

Despite concerns about automated sources being an inexact measure of the population of speeders observed by police, I employ numerous techniques to illustrate that the automated

[30] Another study mentioned in Grogger and Ridgeway (2006), done by the Montgomery County Police Department (2002), used photographic stoplight enforcement to measure the at risk population of speeders. However, this study could not be accessed, so it is uncertain how closely their methodology relates to the current work.

sources do provide a valid population measure. Suggestive evidence using maps of Lafayette and extensive regression controls for location and driver behaviors, as well as propensity score estimates and manipulation of daylight visibility all provide the same conclusion: police officers ticket a larger proportion of African-Americans and women than automated sources. However, the gender effect is larger, and more consistent throughout all methods.

The probability of a ticketed driver being African-American or female is significantly higher when the speeding ticket is given by a police officer in contrast to an automated source, thus implying that police use gender and race as a determining factor in issuing a speeding ticket. Despite the fact that we cannot determine whether the differential treatment is a result of preference-based discrimination or statistical discrimination, the results still illustrate some type of discrimination, which has potential welfare implications.

For example, assume that police ticket African-Americans at a higher rate not because of a taste for discrimination, but because police believe that African-Americans are less likely to contest a speeding ticket. This would mean that higher penalties are levied on African-Americans than whites despite the fact that they have the same offending (speeding) intensity. Given that the incomes of African-Americans are less than half that of whites in this population of speeders,[31] this would constitute a regressive tax based on unequal treatment. Further research is necessary to investigate whether differential contesting rates can explain police behavior, or if preference-based discrimination is really the cause of the disparities between tickets issued by police officers and automated sources.

[31] Based on the zip code analysis previously discussed.

Figure 1
Relative Frequency of Police-Issued Tickets by Speed Over Limit

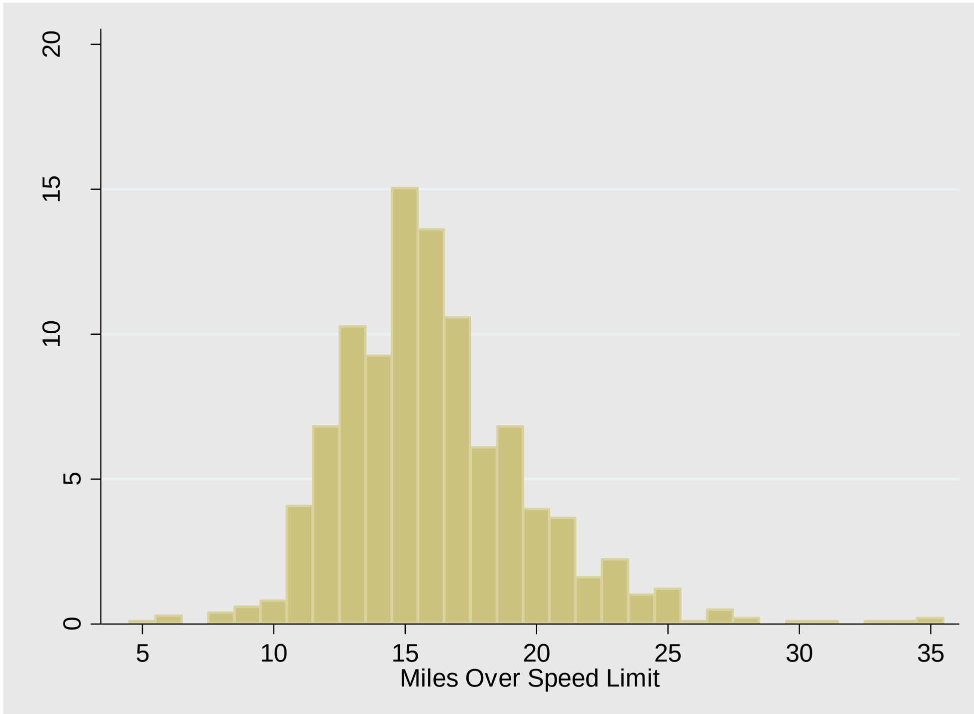

Figure 2
Relative Frequency of Automatic-Issued Tickets by Speed Over Limit

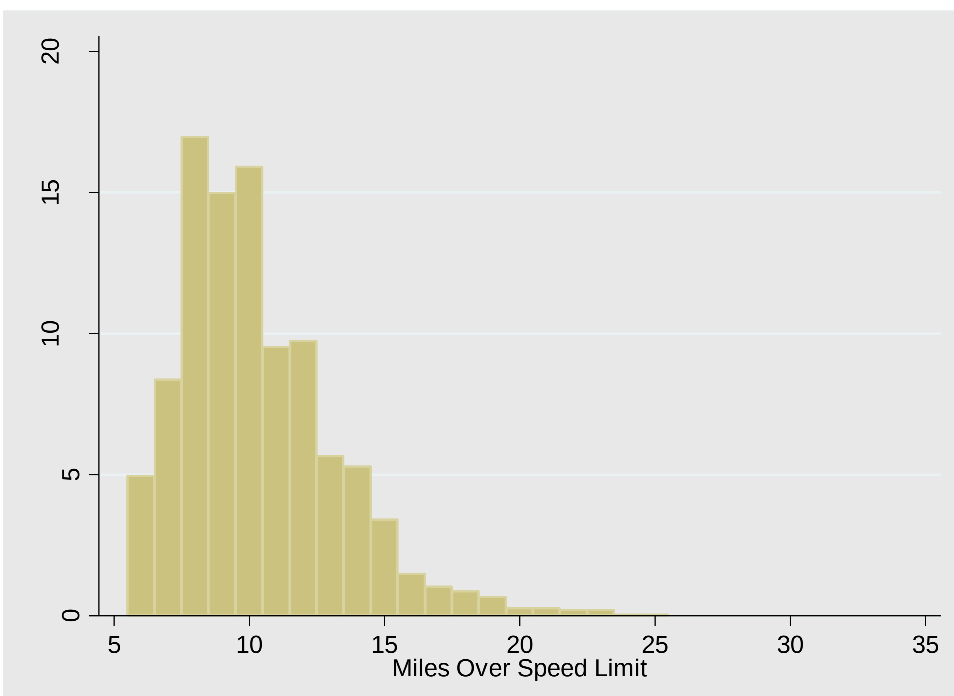

Figure 3
Relative Frequency of Speed Van-Issued Tickets by Speed Over Limit

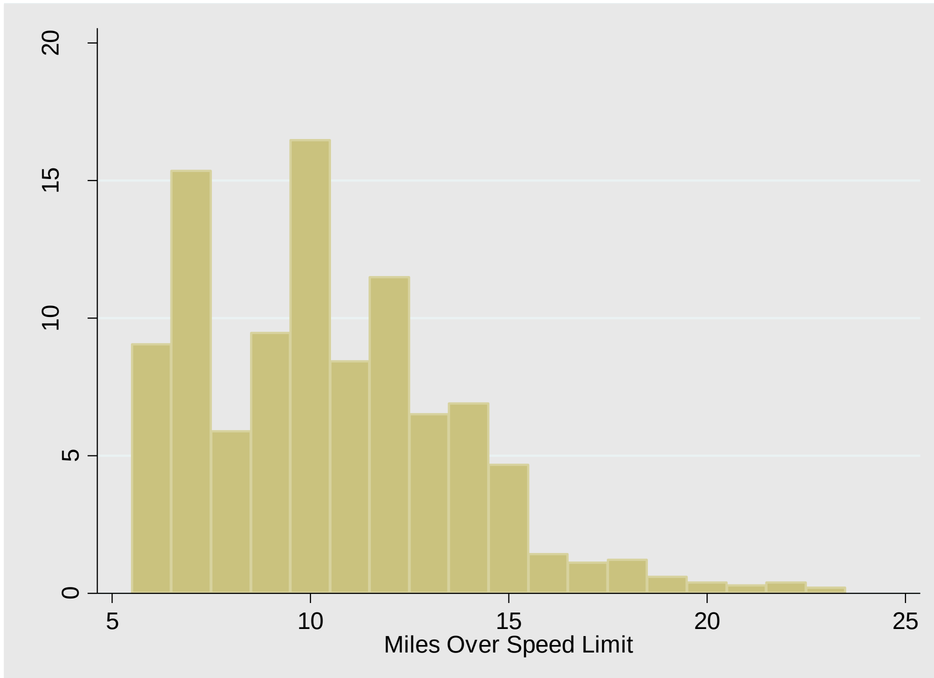

Figure 4
Relative Frequency of Traffic Light Camera-Issued Tickets by Speed Over Limit

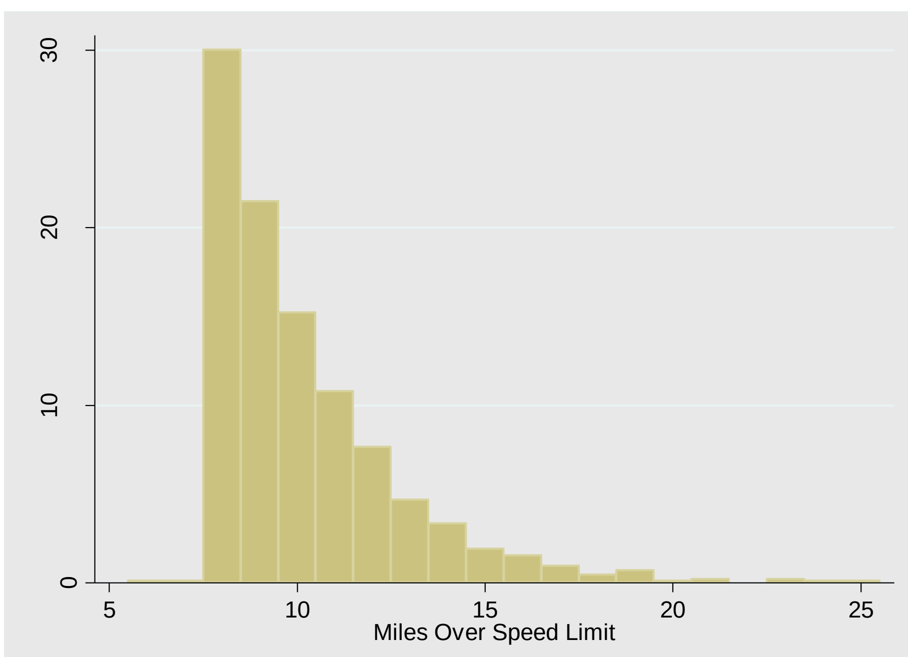

Figure 5
Overall Sample of Tickets Excluding Traffic-Light Issued Tickets

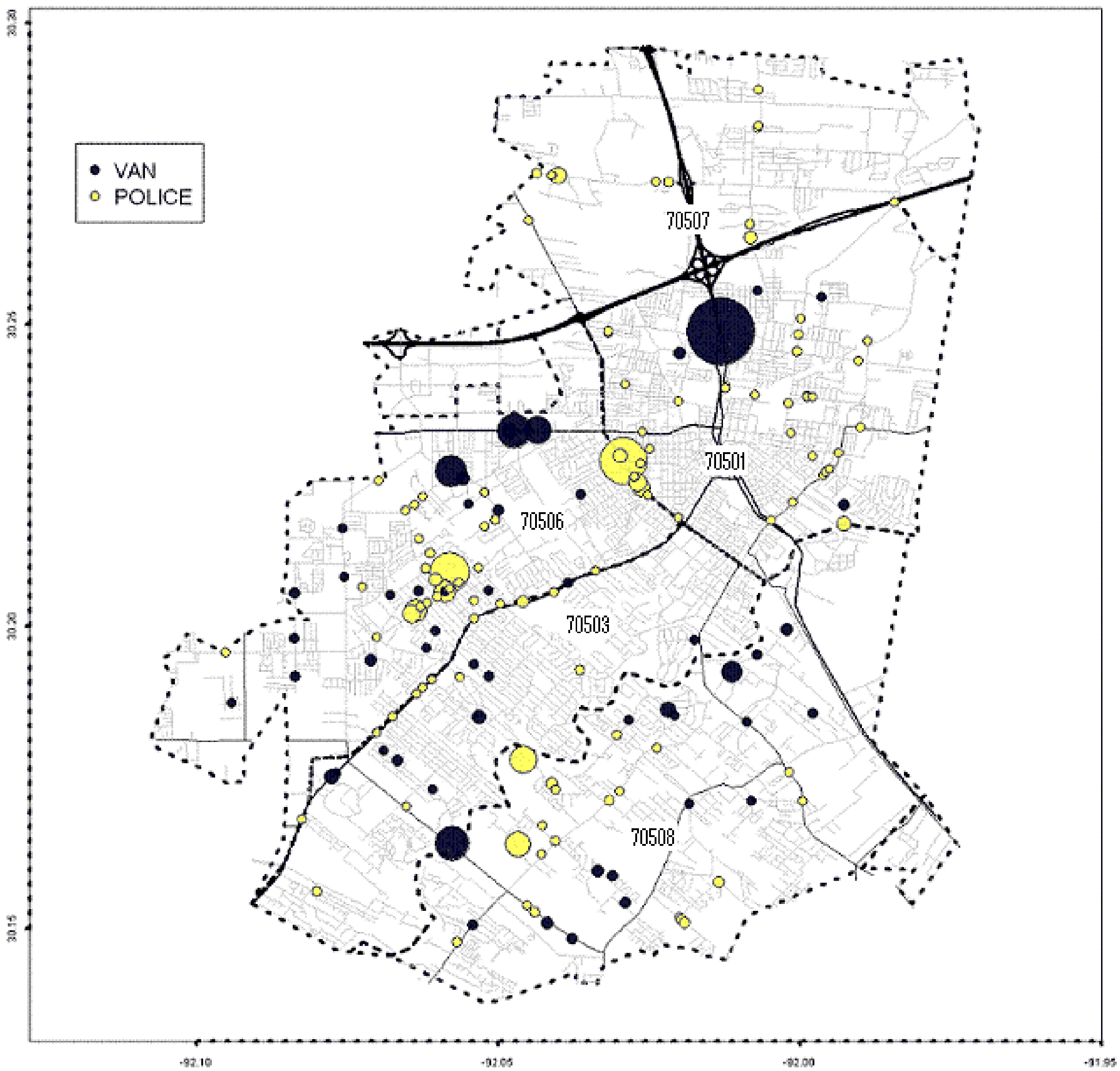

Figure 6: Tickets Used in the Race Estimation Sample

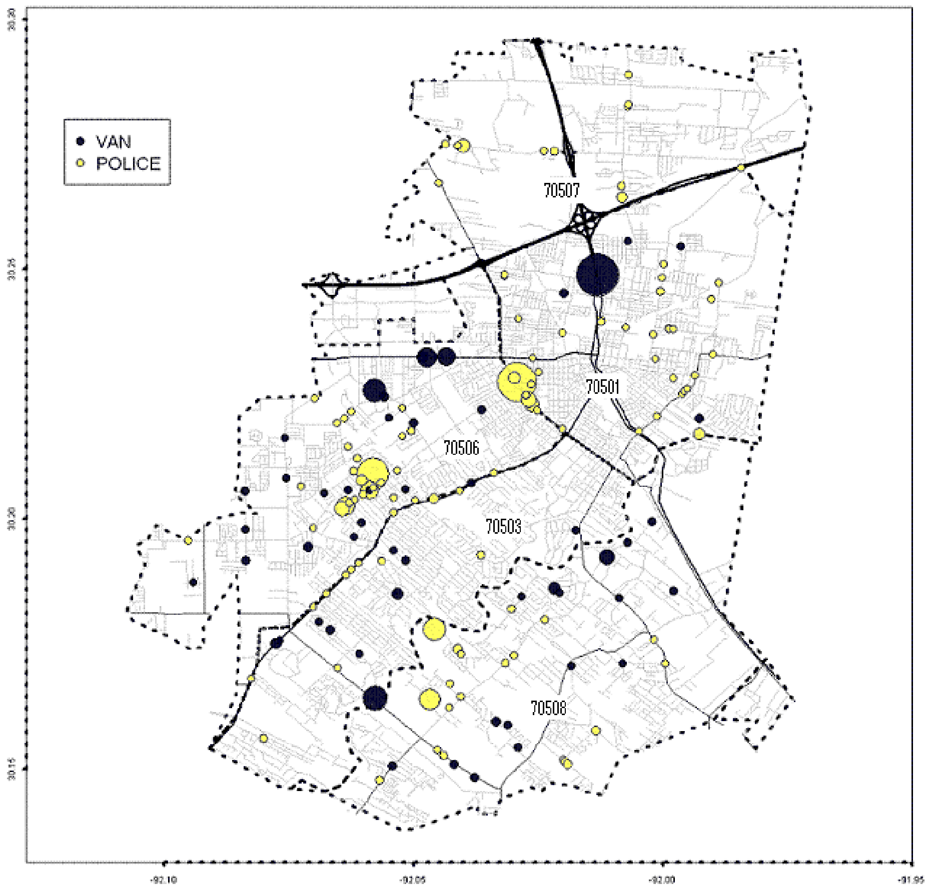

Figure 7: Tickets Used in the Gender Estimation Sample

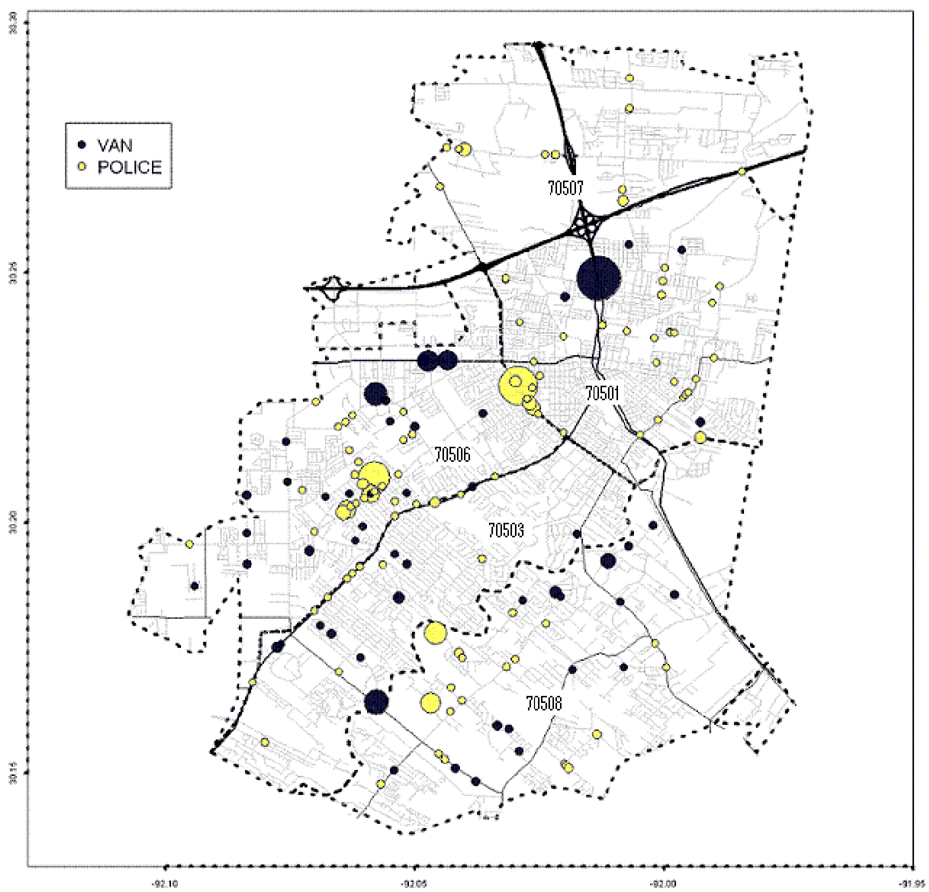

Table 1
Definitions and Descriptive Statistics

Variable	Definition	Observations	Mean	Standard Deviation
Police	Dummy Variable (=1) if the ticket was given by a police officer, 0 otherwise.	2,817	.36	.48
Automated	Dummy Variable (=1) if ticket was given by an automated camera, 0 otherwise.	2,817	.64	.48
African-American	Dummy Variable (=1) if the ticketed driver was African-American, 0 otherwise.	2,408	.26	.44
Female	Dummy Variable (=1) if the ticketed driver was female, 0 otherwise.	2,431	.46	.50
Area 1	Dummy Variable (=1) if ticket was given in Area 1 (zip codes 70501 and 70507), 0 otherwise.	2,799	.50	.50
Area 2	Dummy Variable (=1) if ticket was given in Area 2 (zip codes 70503 and 70508), 0 otherwise.	2,799	.20	.40
Area 3	Dummy Variable (=1) if ticket was given in Area 3 (zip code 70506), 0 otherwise.	2,799	.30	.46
HalfMth 1	Dummy Variable (=1) if violation was given in the first half of the month, 0 otherwise.	2,817	.49	.50
RushHour	Dummy Variable (=1) if violation was given between 7:00 and 8:59 AM or 5:00 and 6:59 PM, 0 otherwise.	2,817	.30	.46
Legal Speed	The speed limit where the ticket was given.	2,795	38.87	9.06
Less than 10 Miles Over	Dummy Variable (=1) if the driver was traveling 10 miles or less over the limit, 0 otherwise.	2,795	.41	.49
11-15 Miles Over	Dummy Variable (=1) if the driver was traveling 11-15 miles over the limit, 0 otherwise.	2,795	.38	.48
16-20 Miles Over	Dummy Variable (=1) if the driver was traveling 16-20 miles over the limit, 0 otherwise.	2,795	.17	.38
More Than 20 Miles Over	Dummy Variable (=1) if the driver was traveling 21 or more miles over the limit, 0 otherwise.	2,795	.04	.21
Speed Trav	The speed the driver was traveling when given a ticket.	2,795	51.23	8.77

Table 2
Means and Standard Deviation, by Area and Ticket Type

	Area 1		Area 2		Area 3	
	Police	Automated	Police	Automated	Police	Automated
African-American	.38**	.32	.14	.14	.21	.21
	(.49)	(.47)	(.35)	(.34)	(.41)	(.41)
	[401]	[796]	[231]	[257]	[346]	[359]
Female	.51**	.39	.55	.50	.58**	.40
	(.50)	(.49)	(.50)	(.50)	(.49)	(.49)
	[402]	[802]	[228]	[256]	[349]	[376]
Legal Speed Limit	29.48**	41.84	36**	39.43	30.81**	47.38
	(7.07)	(5.13)	(4.01)	(8.91)	(7.47)	(7.86)
	[398]	[1009]	[225]	[325]	[343]	[482]
Less than 10 Miles Over	.01**	.56	.04**	.72	.03**	.65
	(.09)	(.50)	(.19)	(.45)	(.18)	(.48)
	[398]	[1009]	[225]	[325]	[343]	[482]
11-15 Miles Over	.37	.38	.38**	.24	.61**	.30
	(.48)	(.49)	(.49)	(.43)	(.49)	(.46)
	[398]	[1009]	[225]	[325]	[343]	[482]
16-20 Miles Over	.49**	.05	.43**	.03	.31**	.04
	(.50)	(.22)	(.50)	(.16)	(.46)	(.19)
	[398]	[1009]	[225]	[325]	[343]	[482]
More than 21 Miles Over	.14**	.01	.16**	.01	.05**	.01
	(.34)	(.08)	(.36)	(.10)	(.22)	(.10)
	[398]	[1009]	[225]	[325]	[343]	[482]
Speed Trav	46.33**	52.61	52.54**	48.72	45.79**	57.47
	(7.62)	(6.62)	(4.94)	(9.96)	(8.37)	(9.37)
	[398]	[1009]	[225]	[325]	[343]	[482]
Half Month 1	.41**	.49	.49	.56	.57**	.44
	(.49)	(.50)	(.50)	(.50)	(.50)	(.50)
	[403]	[1009]	[231]	[325]	[349]	[482]
RushHour	.56**	.24	.09**	.30	.38**	.27
	(.50)	(.42)	(.28)	(.46)	(.49)	(.45)
	[403]	[1009]	[231]	[325]	[349]	[482]

Standard deviations are in (parentheses). The number of observations is in [parentheses]. * denotes a significant difference between the automated and police means at a 10% level, ** denotes significance at a 5% level.

Table 3
Probit Marginal Effects Using Limited Areas

	Dependent Variable: African-American			Dependent Variable: Female		
Sample Zip Codes:	70506 and 70503	70506, 70503, and 70508	70506, 70503, 70508, and 70501	70506 and 70503	70506, 70503, and 70508	70506, 70503, 70508, and 70501
Police	.055**	.022**	.084**	.209**	.153**	.138**
	(.007)	(.001)	(.029)	(.021)	(.001)	(.020)
Area 1			.099**			-.056**
			(.011)			(.004)
Area 2	-.072**	-.061**	-.071**	.042*	.058**	.060**
	(.028)	(.011)	(.010)	(.023)	(.015)	(.009)
HalfMonth 1	.001	-.001	-.008	.047	.055	.029
	(.047)	(.037)	(.025)	(.037)	(.040)	(.034)
LegalSpeed	.002**	.003**	.003**	-.002**	-.003**	-.003**
	(.001)	(.002)	(.001)	(.001)	(.001)	(.000)
11-15 Miles Over	-.002	.022**	.001	-.107	-.075**	-.051
	(.025)	(.008)	(.017)	(.066)	(.029)	(.033)
16-20 Miles Over	.014	.033**	.003	-.100	-.103	-.082
	(.031)	(.000)	(.025)	(.084)	(.074)	(.054)
More than 20 Miles Over	-.055**	.015	-.005	-.237*	-.179**	-.116*
	(.019)	(.050)	(.031)	(.112)	(.029)	(.068)
Rush Hour	-.064**	-.046**	.009	.008	-.047	.064
	(.014)	(.020)	(.071)	(.060)	(.094)	(.065)
9:00-11:59 AM	-.112**	-.098**	-.018	-.001	-.117	-.122
	(.014)	(.000)	(.108)	(.091)	(.183)	(.121)
12:00-2:59 PM	-.130**	-.103**	-.032	-.007	-.088	-.088
	(.016)	(.014)	(.104)	(.064)	(.137)	(.091)
3:00-5:59 PM	-.103**	-.090**	-.033	-.028*	-.091	-.070
	(.032)	(.018)	(.078)	(.017)	(.075)	(.056)
6:00-6:59 PM	.181	.181*	.235**	.096	-.030**	-.092
	(.169)	(.115)	(.108)	(.096)	(.005)	(.096)
Day of the Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	777	1101	1628	795	1114	1646
ln L	-372.61	-506.68	-834.59	-520.34	-741.01	-1098.34
BIC	751.87	1020.36	1683.97	1047.37	1489.03	2211.49

The reported values are the marginal effects, estimated using individual-level data. Robust standard errors, clustered by area, are in parentheses. * denotes significance at a 10% level, and ** denotes significance at a 5% level.

Table 4
Probit Marginal Effects Estimated Using Restricted Samples

Dep. Variable:	African-American		Female	
Sample Used:	Female Tickets	Male Tickets	AA Tickets	White Tickets
Variable				
	I	II	III	IV
Police	.059	.101**	.087	.151**
	(.079)	(.034)	(.100)	(.029)
Area 1	.115**	.111**	-.046	-.053**
	(.011)	(.022)	(.034)	(.013)
Area 2	-.089**	-.078**	.054	.059**
	(.015)	(.026)	(.039)	(.014)
HalfMonth 1	-.050*	.030	-.054	.057**
	(.027)	(.028)	(.038)	(.023)
RushHour	-.048*	.048	-.233	-.051
	(.025)	(.123)	(.171)	(.063)
LegalSpeed	.003*	.003	-.002	-.003*
	(.002)	(.002)	(.001)	(.002)
11-15 Miles Over	-.035	.033	-.077**	-.030
	(.046)	(.033)	(.018)	(.035)
16-20 Miles Over	-.028	.042**	-.101	-.048
	(.075)	(.020)	(.062)	(.070)
More than 20 Miles Over	-.029	-.015	-.047	-.113*
	(.059)	(.062)	(.105)	(.061)
Tuesday	.094**	-.067**	.174**	-.070**
	(.036)	(.031)	(.069)	(.024)
Wednesday	.042**	-.071**	.069	-.127**
	(.020)	(.031)	(.045)	(.024)
Thursday	.050	.003	.049	-.064**
	(.040)	(.031)	(.064)	(.028)
Friday	.043	.035	.069	.017
	(.061)	(.070)	(.186)	(.026)
Saturday	.065	.053**	.057	.004
	(.111)	(.019)	(.135)	(.026)
Sunday	.098	.096*	-.112	-.132**
	(.132)	(.054)	(.204)	(.042)
9:00-11:59 AM	-.097**	.072	-.340	-.087
	(.038)	(.166)	(.197)	(.116)
12:00-2:59 PM	-.143**	.096	-.386**	-.039
	(.052)	(.156)	(.118)	(.110)
3:00-5:59 PM	-.111*	.037	-.283**	-.029
	(.050)	(.101)	(.066)	(.087)
6:00-6:59 PM	.173	.234*	-.217**	-.078
	(.133)	(.147)	(.069)	(.087)
Month FE	Yes	Yes	Yes	Yes
N	774	831	359	1246
ln L	-387.72	-416.49	-234.67	-827.24
BIC	788.74	846.42	481.11	1668.73

The reported values are the marginal effects, estimated using individual-level data. Robust standard errors, clustered by area, are in parentheses. * denotes significance at the 10% level, and ** denotes significance at the 5% level. Month Effects were not significant except October and February in Column II (both at a 10% level of significance), and October and February in Column IV (both at a 5% level of significance).

Table 5
Propensity Score Matching Estimates

	Without Replacement			With Replacement			Radius Matching	
	Random	Ascending	Descending	n=1	n=5	n=10	Caliper, δ=0.001	Caliper, δ=0.01
Female	.150**	.150**	.150**	.215	.375**	.343**	.294**	.273**
	(.063)	(.063)	(.063)	(.188)	(.139)	(.113)	(.048)	(.109)
	922	922	922	946	1029	1112	394	1219
African-American	.081**	.081**	.081**	.049	-.097	.009	.068**	.053
	(.039)	(.039)	(.039)	(.044)	(.233)	(.051)	(.013)	(.045)
	920	920	920	950	1045	1134	441	1238

Standard errors are bootstrapped 500 times. Coefficients are marginal effects of police issued-tickets, clustered by area.

Table 6
Daylight Visibility Means and Standard Deviation of Daylight Controls

	=1, visibility		=0, no visibility	
	Police	Automated	Police	Automated
African-American	.285	.274	.267	.263
	(.452)	(.448)	(.458)	(.452)
	[263]	[106]	[15]	[19]
Female	.551*	.385*	.333	.474
	(.498)	(.489)	(.488)	(.513)
	[265]	[109]	[15]	[19]

Recall that only a subset of police issued tickets are being used: those issued between 6:00 AM and 7:59 AM and those issued between 5:00 PM and 6:59 PM. Standard deviations are in (parentheses). The number of observations is in [parentheses]. * denotes a significant difference between tickets issued by police and those issued by automated sources, at a 5% level.

Table 7
Probit Marginal Effects: Investigating the Effect of Daylight on Police-Issued Tickets

Variable	African-American		Female	
Daylight	.155**	.173**	.311**	.364**
	(.059)	(.059)	(.129)	(.139)
Morning Light	-.017	-.079	.111	.107
	(.220)	(.204)	(.112)	(.132)
Area 1	.185**	.209**	-.117**	-.120**
	(.040)	(.048)	(.050)	(.050)
Area 2	-.012	-.025	-.042	-.081
	(.054)	(.072)	(.114)	(.095)
HalfMonth 1	-.038	-.026	.049	.051
	(.035)	(.027)	(.038)	(.047)
Rush Hour	-	-	-.311	-.356*
			(.163)	(.122)
LegalSpeed	.008**	.008**	.016*	.017*
	(.002)	(.002)	(.009)	(.009)
11-15 Miles Over	-.148**	-.137**	.083	.129
	(.041)	(.061)	(.152)	(.185)
16-20 Miles Over	-.151	-.138	.083	.128
	(.106)	(.117)	(.213)	(.242)
More than 20 Miles	-.109	-.092	.131	.160
Over	(.114)	(.146)	(.137)	(.137)
Tuesday	-.122	-.142	.121	.098
	(.132)	(.129)	(.169)	(.169)
Wednesday	-.143	-.162	.116	.097
	(.118)	(.117)	(.147)	(.161)
Thursday	-.097	-.127	.076	.036
	(.092)	(.077)	(.134)	(.185)
Friday	.027	.005	.175	.167
	(.098)	(.093)	(.158)	(.166)
Saturday	-	-	-	-
Sunday	-	-	-	-
Month FE	No	Yes	No	Yes
N	258	258	265	265
ln L	-144.89	-144.00	-173.53	-171.66
BIC	300.90	299.10	358.22	354.48

The reported values are the marginal effects, estimated using individual-level tickets. Robust standard errors, clustered by area, are in parentheses. * denotes significance at a 10% level, and ** denotes significance at a 5% level. Month FE were not significant except for February (at a 5% level) in Column II.

Table 8
Probit Marginal Effects: Investigating the Effect of Daylight on Automated-Issued Tickets

Variable	African-American		Female	
Daylight	-.173	-.105	-.027	-.057
	(.165)	(.111)	(.125)	(.134)
Morning Light	.178*	.162	.082	.024
	(.104)	(.112)	(.091)	(.114)
Area 1	.271**	.247**	-.281**	-.366**
	(.024)	(.061)	(.015)	(.048)
Area 2	.043	.022	.047	-.040
	(.058)	(.065)	(.053)	(.042)
HalfMonth 1	.018	-.013	.228**	.227*
	(.087)	(.083)	(.109)	(.128)
Rush Hour	-	-	.146	.116
			(.357)	(.406)
LegalSpeed	.002	-.002	-.015**	-.194**
	(.002)	(.006)	(.003)	(.005)
11-15 Miles Over	.022	.078	-.153**	-.164*
	(.086)	(.118)	(.039)	(.089)
16-20 Miles Over	-	-	-	-
More than 20 Miles Over	-	-	-	-
Tuesday	-.059	.005	.166**	.310**
	(.123)	(.110)	(.005)	(.046)
Wednesday	.020	.055	-.119	-.031
	(.146)	(.168)	(.084)	(.107)
Thursday	.311**	.375**	.185**	.304**
	(.103)	(.099)	(.029)	(.046)
Friday	-.161	-.164	.017	.098**
	(.108)	(.078)	(.034)	(.050)
Saturday	-.012	.113	.170	.317
	(.223)	(.206)	(.122)	(.202)
Sunday	.109	.110	-.028	.005
	(.186)	(.215)	(.209)	(.180)
Month FE	No	Yes	No	Yes
N	119	119	126	126
ln L	-63.06	-61.65	-67.68	-65.47
BIC	135.68	132.86	145.03	140.61

The reported values are the marginal effects, estimated using individual-level tickets. Robust standard errors, clustered by area, are in parentheses. * denotes significance at a 10% level, and ** denotes significance at a 5% level. Month FE were not significant except for October, November, and February (at a 5% level) in Column IV.

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