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MAN VS. MACHINE: AN INVESTIGATION OF SPEEDING TICKET DISPARITIES BASED ON GENDER AND RACE

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This paper analyzes the extent to which police behavior in giving speeding tickets differs from the ticketing pattern of automated cameras, which provide an estimate of the population of speeders. The novel data are obtained from Lafayette, Louisiana court records, and provide specific details about the ticketed driver as well as a wide range of violation characteristics. In contrast to the automated cameras, the probability of a ticketed driver being female is consistently and significantly higher when the ticket was given by a police officer. For African-American drivers this effect is less robust, though in general still positive and significant. This implies that police use gender and race as a determining factor in issuing a speeding ticket. Potential behavioral reasons for 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.

JEL classification codes: J71, K42
Key words: gender bias, racial bias, police, ticketing, automated traffic cameras

I. Introduction

Since the seminal work of Becker (1957), which created the theoretical foundation of economics of discrimination, researchers have empirically investigated the existence of discrimination in a variety of settings ranging from wages to murder

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trials.[1] Of particular relevance to the present work is the investigation of racial and gender bias of police in motor vehicle searches and ticketing for driving violations, which is costly to innocent individuals of a targeted race or gender (Durlauf 2006). As a result of little to no external validity of studies across different police departments, findings are mixed: some researchers find evidence of racial and/or gender discrimination (Antonovics and Knight 2009, Blalock et al. 2007, Makowsky and Stratmann 2009, Anwar and Fang 2006), 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 detailed, unique data from automated speed detection to measure differences in the proportion of speeding tickets issued to gender and racial groups in Lafayette, Louisiana. 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 strong, statistically significant evidence that police consider gender when deciding to ticket speeders, and some evidence that race is also a factor even when accounting for potential endogeneity of the location of officers and automated sources.

In the context of this analysis, it is impossible to distinguish between tastes versus statistical motives for differential ticketing; however, the first-order issue is whether or not these types of behaviors exist at all. Preference-based discrimination means police derive an additional non-monetary benefit by ticketing these individuals. 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 considered more dangerous, more likely to change their future behavior as a result of the stop, or even more likely to pay a speeding ticket fine instead of going to court to contest it (Blalock et al. 2007). Though taste for discrimination cannot be ruled out, later I present evidence that police behave rationally in that they issue tickets more frequently to those who speed 16 miles an hour or more over the limit (rather than those who were only traveling 5-15 miles an hour above the speed limit), which is associated with higher fines.

[1] 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.

Researchers approach the question of police discriminatory behavior by utilizing variations of two general methods: the outcome test approach and the benchmarking test approach (Becker 1957, Anwar and Fang 2006). Mainly utilized in stop and search related questions, the outcome test approach is best explained by considering the work of Knowles, Persico, and Todd (2001). Utilizing highway data from Maryland, they illustrate equal success rates for searches of motor vehicles driven by African-Americans and whites despite the fact that more searched cars are driven by African-Americans. This implies police are engaging in statistical discrimination: once a car has been stopped, police are more likely to search if the driver is African-American because, on average, it is more likely that they will find drugs or contraband. Race is statistically related to likelihood to carry drugs. However, Antonovics and Knight (2009) use the same dataset and find that if the officer's race is different from that of the offender, the vehicle is more likely to be searched, implying a motive of preference-based discrimination. The outcome test approach requires data which provides two stages: for example, which driver and cars are stopped and then, of those, which cars are subsequently searched.

The benchmarking test compares a population to the sample of interest to determine if the sample ticketed by police is different by race or gender, all else equal. One drawback of this approach is the inability to distinguish between preference- based and statistical discrimination, however, the current paper provides a distinct advantage over previous literature due to the richness and reliability of the population data. In previous studies, the benchmarking test approach has not been reliable due to the denominator problem, which occurs if the "benchmark" used is not the same population observed by police. For example, comparing the population of all drivers in a city to those ticketed by police may not be reliable if the population of drivers committing an offense differs from the city driver population by race and/or gender. Then, the underlying comparison and any conclusions drawn would be invalid.

For the present work, the automated tickets provide an entirely objective measure of the speeding population in a given location where every speeding car that passes receives a ticket, and from which police ticket a subsample of drivers. Due to the uniqueness of this dataset, the denominator problem is eliminated. This assumption is reinforced in Section VI where I employ a similar methodology to Grogger and Ridgeway (2006), who utilize differences in daylight savings time to compare tickets issued by police during daylight to those issued during darkness, when race is likely unobservable. They find no significant evidence of racial profiling in Oakland, California, whereas I find evidence consistent with my main results, reinforcing the validity of using automated cameras as the population measure for police-issued tickets.

The method of data collection itself can be a problem for either approach: if police do not report all incidents of tickets or stops, analyses will be biased. This issue is referred to as nonreporting, and is a consistent problem within the literature (Grogger and Ridgeway 2006, Knowles et al. 2001, Persico and Todd 2007). Mainly arising in conjunction with post-lawsuit data (Grogger and Ridgeway 2006, Blalock et al. 2007, Knowles et al. 2001, Persico and Todd 2007, and Makowsky and Stratmann 2009), nonreporting occurs because police officers are legally required to record all stops, not only the ones which result in a ticket. However, in an effort to avoid repercussions from the lawsuit and suspected racial discrimination, police officers may change their behavior as a result of the knowledge of data collection.[2] For example, Makowsky and Stratmann (2009) find that Hispanics are more likely to be fined, but there is no difference in fines issued to African-American drivers, which they state may be a product of widespread knowledge of the study and data collection by the police department.[3] 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).[4] The dataset used in this paper has a distinct advantage because the data were collected after the speeding tickets were given, include every ticket issued by police officers during the sample period with no prior knowledge by police officers, and thus avoids the problem of post-lawsuit data.[5]

II. Data source and descriptive statistics

Lafayette, Louisiana is a city in southern Louisiana with a population of 120,623, about 60 miles west of Baton Rouge (Census 2010). About 64% of Lafayette residents

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[2] Data collection typically begins after the lawsuit is filed.

[3] Due to this potential change in police behavior, studies which employ post-lawsuit data provide a lower-bound estimate of the extent of racial/gender profiling. That is, if police officers change their behavior in order to avoid punishment or stigma, the results obtained from the analysis of post-behavioral change data will reflect a lower amount of racial or gender bias than truly exists.

[4] A related problem is the omitted variables problem, where police may observe something which the researcher cannot: behavior of the driver, for example. This problem exists for both the outcome approach and the benchmarking approach insofar as this omitted variable is related to race or gender.

[5] Even without a formal lawsuit it is important that police had no suspicion that this type of study might occur, so that they would not intentionally alter their behavior. There is no history of legal action taken against the police department in Lafayette, however, the issue of racial profiling within Louisiana has been of interest to the media after the period of data used in this analysis. For instance, a 2009 report by the American Civil Liberties Union claims there is widespread racial profiling in Louisiana, and House Representative Rickey Hardy of Lafayette (unsuccessfully) pushed a bill requiring police to track the race of individuals stopped for traffic violations in 2010 (Pierce 2010). No substantial policy or news changes came as a result of either of these publications.

are white and about 31% African-American. Lafayette encompasses five zip codes, 70501, 70503, 70506, 70507, and 70508. Each of these areas has quite different characteristics. Specifically, 71.8% of 70501 residents are African-American, as opposed to 70503 and 70508, where less than 11% of residents are African-American (Census 2010). The gender composition throughout the city does not vary significantly between zip codes, ranging from 47.7% male to 48.9% male (Census 2010). 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 $15,491, while in the wealthiest areas (70508 and 70503) it is nearly $38,000 (Census 2007-2011).

Lafayette began implementing automated speed cameras in October 2007, with the help of Redflex, the company who 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 in the following subsections.

A. Lafayette City 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.[6] The database includes information on the ticketed individual (date of birth, race, gender), the badge and name of the police officer who wrote the ticket, time, place, legal speed limit, and speed traveled at the time of the violation.[7] Police officers use discretion in issuing speeding tickets, but do not have any influence over the fine charged for a specific violation. Instead, Lafayette City Court sets fines. This is vital in understanding potential discrimination in this setting, especially in reference to existing research where police motives in issuing tickets may also affect the fine amounts (Makowsky and Stratmann 2009, for example).

Previous studies have utilized officer variation to aid in identifying the type of discrimination occurring, if it is occurring, however, the majority of officers in the

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[6] In the Lafayette City Court computer database, speeding violations are specifically coded as 86-incident number. When a speeding ticket is reduced to a lesser charge, it is coded as a speeding ticket amended to something else (seatbelt violation for example). Tickets given outside of the city limits or given by State Troopers in the city limits are not in this database.

[7] Information specific to the offender is taken from the driver's license and officer observation. More specifically, name, gender, age, and home address are printed on Louisiana licenses, but race is not. Officers input driver race when they issue a ticket, which is also input into the computer system and provided in the dataset.

Lafayette Police Department are white males (Antonovics and Knight 2009 and Anwar and Fang 2006). Even more strikingly, less than 3% of tickets were given by officers who are not white males. Due to lack of variation of officer characteristics it is not useful to control for the officer's race or gender in the analysis.

B. Automated tickets

Lafayette Consolidated Government, and not the police department, decided to implement the Redflex program[8] and oversee its technology in an attempt to improve traffic safety. 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 also in "speed vans" which park at different locations throughout the city to catch speeders. Tickets issued by the fixed cameras will not be included in the present analysis because they likely induce changes in speeding behavior for two main reasons: these locations are publicized and well known so drivers will intentionally drive safer to avoid being fined[9] and they are at intersections where drivers likely are more cautious as opposed to other stretches of the same road.

The program began in October 2007 with two speed vans giving citations at about 35 different locations in Lafayette. Though the automated ticketing system still continues today, the sample period used in this paper only extends to February 2008. Over the sample period, October 2007 to February 2008, 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 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. On a particular day and at specific times, the vans are told to locate at randomly selected locations from the overall list, but the public is not informed of these decisions.

Outwardly, speed vans provide a close comparison to police cars (officers). Speed vans move around Lafayette randomly and individuals cannot predict their locations, nor are they significantly easier to identify than a police car. Therefore, drivers should behave in the same manner around police cars and speed vans. In

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

[9] 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.

opposition to police, cameras on the vans are completely automatic, and take photographs whenever they detect a car that is traveling faster than the speed limit. As soon as the cameras detect a speeder, four photographs are taken: one of the driver, one of the car's license plate, and two of the general area of the car at the time of the violation. Once an individual has been "caught" by the speed cameras, a paper ticket is issued to the car's registered owner (the assumed driver of the car). The automated database contains every ticket given by speed vans. Lafayette Consolidated Government officials estimate that about five to ten percent of the time, the person driving is not the car's registered owner. When someone is issued a ticket, but they were not actually driving, they have two options: pay the ticket anyway, or refute the ticket by naming the actual driver of the car. When a ticket is refuted, it is reissued to the individual who was named as the driver. 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.[10]

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 traveled. Gender and race can be inferred from the four pictures on each ticket, most importantly, two of the driver.[11] Since automated tickets are easier to give and require less manpower, they are issued much more frequently than police tickets. During the period of October 2007 to February 2008 the average number of automated tickets is 3,100 per month.

C. Data

The sample includes speeding tickets 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 inferred, a 15% random sample was chosen from the population of automated tickets. Because of little or no visibility of individual drivers at night, only daytime tickets are used in the main analysis so that race and

[10] 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.

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

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 23% of ticketed drivers are African-American and 48% are female. Since the socio-economic characteristics of some of Lafayette's zip codes are drastically different and driving behavior also may differ from area to area, much of the analysis controls for the zip code where the ticket was issued. The majority of tickets are issued in 70506, with nearly one-third issued in the poorest zip code (70501). The average ticketed driver was traveling about 52 miles an hour, with 72% 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 zip code and source of ticket. The subjective nature of police-issued tickets means that some variables will differ by source: police can only ticket a subsample of the population of speeding drivers, and as such target higher speeders, in lower speed zones (often neighborhoods). For instance, the variables which measure how fast an individual was traveling (*Less than 10 Miles Over, 11-15 Miles Over, 16-20 Miles Over and More Than 20 Miles Over*) illustrate an important difference between the automatically issued tickets and police tickets: the majority of automated tickets are issued at lower severities of speeding.[12] Conversely, most police issued tickets are given in the *16-20 Miles Over* range. Individuals who receive tickets for higher speeds must pay a higher fine,[13] which results in higher revenues for the City of Lafayette, and in turn, likely a higher budget for the police department (Makowsky and Stratmann 2009).

These differences may arise in part because of the different costs faced by automated cameras versus police in 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. However, it is important to remember that these differences do not violate the underlying assumption: the automated sources capture the population of speeders whereas the police are ticketing a subsample of that population. Further evidence of the validity of this assumption will be provided in Sections III and VI.

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

[13] 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.

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.	1,914	.49	.50
Automated	Dummy Variable (=1) if ticket was given by an automated camera, 0 otherwise.	1,914	.51	.50
African-American	Dummy Variable (=1) if the ticketed driver was African-American, 0 otherwise.	1,663	.23	.42
Female	Dummy Variable (=1) if the ticketed driver was female, 0 otherwise.	1,681	.48	.50
70501	Dummy Variable (=1) if ticket was given in zip code 70501, 0 otherwise.	1,896	.32	.47
70503	Dummy Variable (=1) if ticket was given in zip code 70503, 0 otherwise.	1,896	.10	.30
70506	Dummy Variable (=1) if ticket was given in zip code 70506, 0 otherwise.	1,896	.39	.49
70508	Dummy Variable (=1) if ticket was given in zip code 70508, 0 otherwise.	1,896	.19	.40
HalfMth 1	Dummy Variable (=1) if violation was given in the first half of the month, 0 otherwise.	1,914	.52	.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.	1,914	.35	.48
Legal Speed	The speed limit where the ticket was given.	1,892	38.63	10.89
Less than 10 Miles Over	Dummy Variable (=1) if the driver was traveling 10 miles or less over the limit, 0 otherwise.	1,892	.30	.46
11-15 Miles Over	Dummy Variable (=1) if the driver was traveling 11-15 miles over the limit, 0 otherwise.	1,892	.42	.49
16-20 Miles Over	Dummy Variable (=1) if the driver was traveling 16-20 miles over the limit, 0 otherwise.	1,892	.22	.42
More Than 20 Miles Over	Dummy Variable (=1) if the driver was traveling 21 or more miles over the limit, 0 otherwise.	1,892	.05	.22
Weekday	Dummy Variable (=1) if the ticket was issued on a weekday (M,T,W,T,F), 0 otherwise.	1,914	.81	.40
Speed Trav	The speed the driver was traveling when given a ticket.	1,892	51.72	10.24

Table 2. Means and standard deviation, by area and ticket type

	70501		70503		70508		70506	
	Police	Automated	Police	Automated	Police	Automated	Police	Automated
African-American	.35**	.27	.07	.14	.15	.13	.21	.22
	(.47)	(.44)	(.26)	(.35)	(.36)	(.34)	(.41)	(.41)
	[331]	[201]	[15]	[145]	[216]	[112]	[346]	[279]
Female	.50**	.32	.60	.47	.54	.55	.58**	.36
	(.50)	(.47)	(.51)	(.50)	(.50)	(.50)	(.49)	(.48)
	[332]	[205]	[15]	[146]	[213]	[110]	[349]	[293]
Legal Speed Limit	27.52**	48.70	31.54**	40.37	36.27**	38.34	30.81**	49.16
	(5.59)	(4.99)	(5.55)	(8.29	(3.74)	(9.48)	(7.47)	(7.77)
	[328]	[270]	[13]	[174]	[212]	[151]	[343]	[388]
Less than 10 Miles Over	.01**	.29	.23**	.67	.02**	.77	.03**	.62
	(.10)	(.45)	(.44)	(.47)	(.15)	(.42)	(.18)	(.49)
	[328]	[270]	[13]	[174]	[212]	[151]	[343]	[388]
11-15 Miles Over	.38	.63	.54*	.29	.37**	.19	.61**	.32
	(.49)	(.48)	(.52)	(.45)	(.48)	(.40)	(.49)	(.47)
	[328]	[270]	[13]	[174]	[212]	[151]	[343]	[388]
16-20 Miles Over	.51**	.07	.15**	.03	.45**	.02	.31**	.05
	(.50)	(.26)	(.38)	(.18)	(.50)	(.14)	(.46)	(.21)
	[328]	[270]	[13]	[174]	[212]	[151]	[343]	[388]

Table 2. (continued) Means and standard deviation, by area and ticket type

	70501		70503		70508		70506	
	Police	Automated	Police	Automated	Police	Automated	Police	Automated
More than 21 Miles Over	.10**	.01	.08**	.01	.15**	.01	.05**	.01
	(.02)	(.01)	(.28)	(.08)	(.37)	(.11)	(.22)	(.10)
	[328]	[270]	[13]	[174]	[212]	[151]	[343]	[388]
Weekday	.99**	.70	.80	.72	.95**	.80	.99**	.5
	(.08)	(.46)	(.41)	(.45)	(.21)	(.40)	(.12)	(.50)
	[333]	[270]	[15]	[174]	[216]	[151]	[349]	[388]
Speed Trav	43.94**	60.93	45.00*	50.02	53.00**	47.23	45.79**	59.35
	(5.58)	(6.23)	(5.20)	(9.50)	(4.54)	(10.28)	(8.37)	(9.47)
	[328]	[270]	[13]	[174]	[212]	[151]	[343]	[388]
Half Month1	.44	.45	.80*	.57	.47	.54	.57	.55
	(.50)	(.50)	(.41)	(.50)	(.50)	(.50)	(.50)	(.50)
	[333]	[270]	[15]	[174]	[216]	[151]	[349]	[388]
RushHour	.66**	.28	.13	.29	.09**	.32	.38**	.30
	(.48)	(.45)	(.35)	(.45)	(.28)	(.47)	(.49)	(.46)
	[333]	[270]	[15]	[174]	[216]	[151]	[349]	[388]

Note: 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.

III. Validity of automated tickets as a measure of the population

In order for the automated issued tickets to provide a valid comparison group to police issued tickets, both ticketing sources must observe the same driving (speeding) population. Police witness the population of speeders in a given location, but are only able to ticket a select number, while the automated cameras ticket the entire population of speeders in that location objectively. If police do not observe the same population, any difference in ticketing may be the result of the different population of speeders and not due to a difference in ticketing behavior. There are some procedural differences that need to be considered, but overall, the populations being measured are shown to be comparable. I first provide convincing descriptive evidence below, and then in Section VI more explicitly account for endogeneity concerns with 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 locating procedures of 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 number 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.[14]

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. Importantly, officers are told where to locate according to precincts in Lafayette, generally: north, south, east or west. More specifically, when complaints have been filed about speeders in specific neighborhoods or areas within this distinction, traffic officers are told to

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[14] 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.

focus on these areas for the duration (or the majority) of their shift.[15] There is always an officer in each area of the city.[16] Therefore, how police are located to give tickets should not be influenced by preferences to ticket a specific type of individual, because they are told in which areas to locate for each shift.

Although the mobile automated cameras are randomly assigned to a location during the day, the locations themselves are not completely random. First of all, 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). Since "safe" locations include different types of roads, this should not cause any problem in comparing to police issued tickets since 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 comprised areas known to have speeding problems; and as such, tended to be busier streets instead of neighborhood roads. Similarly, because the goal of this program was to reduce speeding, the areas that would have the most impact on speeders tended to be busier city streets, as compared to neighborhood roads. 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 could request a van be placed in their neighborhood, these neighborhood locations were added to the list, but the number 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, and specifically near schools. In school zones, the legal speed a car can travel 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 nearby these same areas.[17] The next section empirically investigates this claim.

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[15] Though the data do not specify the difference between the two existing types of officers (traffic and patrol), it is obvious that the officer on duty was sent specifically to target speeders when he/she gives numerous tickets in the same location in a short period of time. Traffic officers issue the most speeding tickets, on occasion a patrol officer will observe someone speeding in their area, and give a ticket.

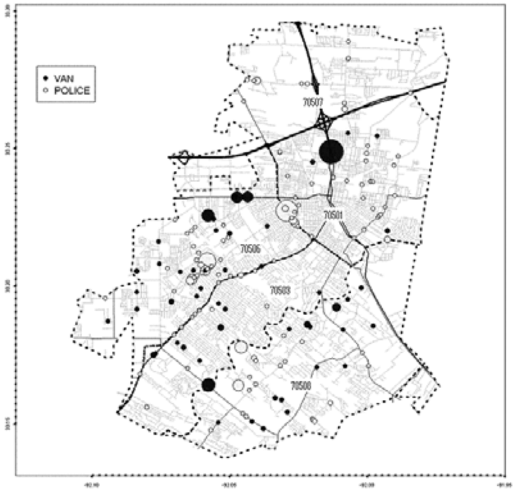
[16] The Lafayette Police Department provided the information in the preceding paragraph through personal communication.

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

The ideal measure of the speeding population that police observe would be to consider drivers at the exact locations where police issue tickets, but this is not feasible for multiple reasons. The most obvious of these reasons is that if automated sources and police chose to locate at the exact 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 Figures 1 and 2, there are some instances where an automated camera and police officer ticketed a speeder in the exact 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.

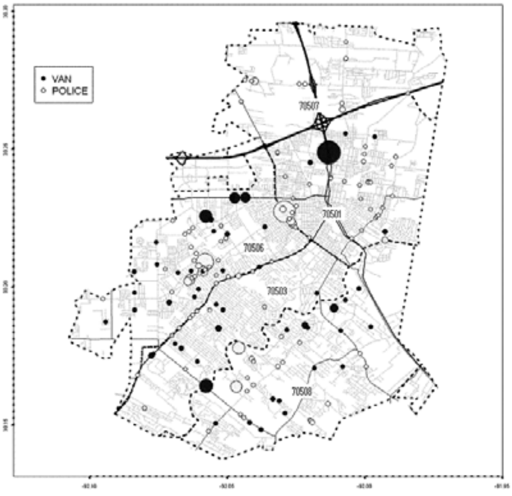
Figures 1 and 2 show the city of Lafayette, with dots representing the frequency of tickets issued by each ticketing source, at specific locations. The dots are sized proportionately to the frequency of tickets that were issued at that location.[18] For example, in many instances only one ticket is issued in a location and these dots are the smallest on Figure 1.

Figure 1. Tickets used in the race estimation sample



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

Figure 2. Tickets used in the gender estimation sample



The western portion of the map, which includes zip codes 70506 and 70503, illustrates a fairly equal coverage of mobile vans and police officers. Since there are automated vans and police officers in near proximity to one another (and, generally on similar road types), it is feasible to assume that both ticketing sources are observing the same population of speeders, when controlling for time of day, and other incident characteristics. While there is a greater discrepancy between police and automated ticket locations of the remaining zip codes, 70501 and 70508, tickets are still issued within blocks of each other. The 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. Additional robustness checks in Section VI provide supportive evidence that the automated tickets remain a valid measure of the speeding population in these areas as well.

The area encompassing zip code 70507, north of Interstate 10, is excluded from the analysis because no speed van tickets were issued in this area during the sample period. Without an accurate measure of the speeding population, a reliable analysis cannot be conducted. This area of the city does not include the main commercial areas and only 77 police-issued tickets are dropped as a result of this exclusion.

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.

In a novel paper, Eeckhout, Persico, and Todd (2010) explore the practice of random crackdowns by police and find that these crackdowns are efficient for crime reduction in the context of automated traffic monitoring. One important distinction from the current work is that individuals in Lafayette are not notified of which roads the automated vans will be located: the "crackdowns" are unknown. Though the use of automated cameras likely reduces speeding on the whole, as found in Eeckhout, Persico, and Todd (2010), it should not impact the validity of comparing police to automated tickets since both observe this reduction simultaneously.

IV. Methods

The ideal way to investigate if police give speeding tickets differentially based on gender or race is to have information on the entire population of speeders, then to compare the population of speeders with those who are ticketed. 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. The automated ticket system provides a measure of the speeding population in a given location, since the cameras ticket all speeding cars in that area. This also provides an advantage over previous literature, where population measures are not completely objective.[19] 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 tickets issued by police and tickets issued by vans.

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

[19] 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.

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 or not 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)

$$B_i = \alpha + X_i'\beta + \gamma Pol_i + \varepsilon_i, \tag{1}$$

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 otherwise (if the ticket was given by an automated source). In this specification, if the coefficient of the dummy variable for a police-given ticket (γ) is positive and statistically significant, this implies that race (or gender) does play a role in a police officer's decision to pull over and ticket a speeder.

V. Results

Table 3 provides regression results for the whole sample of tickets as well as for subsamples based on street-type where the ticket was issued. The entries are marginal effects; and robust standard errors, clustered by zip code, are reported in parentheses. All columns control for zip code fixed-effects, whether the ticket was given in the first half of the month, whether the ticket was issued during rush hour in the morning or evening, 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*), whether the violation occurred on a weekday, and fixed effects for time blocks during the day.[20]

[20] Estimates for each zip code individually can be provided upon request. There is no significant effect of police for African-American tickets, but it is more likely that a ticketed individual will be female if the ticket was issued by a police officer for one zip code. Similarly, if no area controls are included the police coefficient is not statistically significant for African-Americans, but remains significant when considering gender.

Table 3. Probit marginal effects by street type

	Dependent Variable: African-American			Dependent Variable:Female		
	Entire Sample	Main City Streets	Neighborhood Streets	Entire Sample	Main City Streets	Neighborhood Streets
Police	.077**	-.014	.040	.135**	.195**	.338**
	(.025)	(.076)	(.091)	(.056)	(.096)	(.121)
70503	-.143**	-.080	-.279***	.106**	.080	.209
	(.007)	(.047)	(.033)	(.025)	(.074)	(.128)
70506	-.091**	-.007	-.256**	.054**	.001	.118
	(.007)	(.042)	(.103)	(.009)	(.053)	(.133)
70508	-.144**	-.024	-.142	.119**	.052	-.055
	(.009)	(.055)	(.065)	(.021)	(.073)	(.155)
HalfMonth 1	-.010	.024	.005	.025	.012	-.009
	(.023)	(.031)	(.048)	(.022)	(.040)	(.059)
Rush Hour	.009	.035	-.017	-.061	-.125	.026
	(.069)	(.064)	(.050)	(.071)	(.077)	(.063)
LegalSpeed	.002**	.001	.001	-.004**	-.009	.000
	(.001)	(.004)	(.005)	(.001)	(.006)	(.008)
11-15 Miles Over	.004	.078**	-.088	-.054	-.060	-.267**
	(.023)	(.038)	(.099)	(.051)	(.046)	(.128)
16-20 Miles Over	.011	.004	-.091	-.079	-.038	-.217
	(.028)	(.063)	(.090)	(.052)	(.076)	(.138)
More than 20 Miles Over	.001	.095	-.168*	-.120	-.129	-.060
	(.034)	(.109)	(.060)	(.079)	(.101)	(.195)

Table 3. (continued) Probit marginal effects by street type

	Dependent Variable: African-American			Dependent Variable:Female		
	Entire Sample	Main City Streets	Neighborhood Streets	Entire Sample	Main City Streets	Neighborhood Streets
Weekday	-.064	-.057	-.057	.007	-.042	.070
	(.042)	(.037)	(.136)	(.025)	(.045)	(.163)
9:00-11:59 AM	-.018	-.029		-.108	-.154	
	(.098)	(.069)		(.126)	(.091)	
12:00-2:59 PM	-.034	.001		-.085	-.150	
	(.097)	(.072)		(.102)	(.091)	
3:00-5:59 PM	-.037	-.030		-.070	-.090	
	(.069)	(.060)		(.074)	(.082)	
6:00-6:59 PM	.236**	.258**		-.088	-.031	
	(.106)	(.119)		(.206)	(.114)	
N	1628	697	340	1646	711	343
ln L	-836.11	-342.12	-164.58	-1105.99	-460.77	-229.24
BIC	1694.4	788.98	399.10	2234.20	1026.60	528.54

Note: The reported values are the marginal effects, estimated using individual-level data. Robust standard errors, clustered by zip code, are in parentheses. * denotes significance at a 10% level, and ** denotes significance at a 5% level. Time block was excluded from neighborhood regressions because if included 6:00 to 6:59 perfectly predicted driver race and gender. Even when included results are qualitatively the same.

Columns I and IV include all zip codes except for 70507, where no automated van tickets are issued. However, the remaining columns restrict the sample based on the type of street where the ticket was issued to better control for potential differences in exposure to police and differences in driving populations. *MainCityStreets* are comprised of tickets issued on major two to four lane roads within Lafayette: Johnston Street, Ambassador Caffery Parkway, Kaliste Saloom Road, and Pinhook Road. The regression results using the sample including clusters of police and automated tickets issued on *NeighborhoodStreets* are presented in Columns III and VI.

The police coefficient is positive and significant in the first column, 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. However, when controlling more specifically for road type the police coefficient is no longer significant.

When *Female* is the dependent variable, the police coefficient is positive and significant for all regressions, though this impact is larger for tickets issued on neighborhood roads (.34 as opposed to .195 for city streets). The police coefficient of the estimates utilizing the entire sample indicates that conditional on being issued a ticket, the probability of a speeding ticket being received by a female is nearly 14 percentage points higher when the ticket was issued by a police officer.[21] Anecdotally, individuals tend to believe that men receive more tickets than women,[22] but the data illustrate that this is not the case. Blalock et al. (2007) also found that women were more likely to be ticketed than men in three of five study locations.

In order to identify differences in ticketing by source, I control for a number of variables important for driving patterns and population as well as violation severity. Zip code fixed effects are important if the racial or gender makeup of those areas are vastly different, based on living areas or travel patterns. These are most important for race, as seen in the negative coefficients, since compared to 70501 relatively fewer African-Americans are receiving tickets. *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. In a similar vein, *RushHour* and

[21] 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.

[22] For example, in a college-student survey, Blalock et al. (2007) found that the majority of respondents believed a man would more likely be ticketed than a woman if both were stopped for speeding 12 miles over the limit.

Weekday should capture any differences in driving population differences by time of day or work patterns, but both are insignificant in all specifications.

Legal speed where the ticket is issued acts as a proxy for road type, which better explains why it is significant only when estimated using the entire ticket sample. The subsequent columns explicitly control for road type, rendering this control insignificant. 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.[23]

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), specific time of day variables are also included in the main specification. The additional hour dummy variables are: *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,* but are not consistently significant across specifications.

The same analysis was performed utilizing police precincts instead of zip codes as the area identifier, where the police coefficient is still positive, significant, and nearly the same magnitude as earlier estimations. Controlling for police precincts should reduce any impact of differential exposure to police based on area of patrol (since police patrols are assigned according to precincts). This is especially important given the importance of location in an officer's decision to stop a driver (Sanga 2014). Results are provided in Appendix Table A2.[24]

These results provide more evidence that police consider gender when issuing speeding tickets, but introduce doubt into the likelihood of police consideration of

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[23] A question may arise as to how the severity of the violation impacts these results. If the ticketed drivers included in the regression sample are restricted to those traveling 11 miles or more over the limit, the majority of the results remain consistent to estimations including the entire sample of ticketed drivers. However, the police coefficient is no longer significant when the dependent variable is *African-American*. It is not necessarily the case that there will be greater evidence of racial and/or gender bias when considering these more dangerous speeders. In fact, as cited in other existing literature (Blalock et al. 2007), there is some evidence supporting the idea that police discrimination decreases as the offense severity increases; in this case, for example, for more severe crimes police are less willing to focus on gender and instead the desire to punish the bad behavior regardless of the offenders' gender strengthens.

[24] All specifications were also run including interaction terms between police and zip code dummies. The overall results are consistent, though the police marginal effect is stronger in 70501 and 70506 for both gender and race estimates. Similarly, including 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. Lastly, specifications were run excluding tickets issued in December, since this month may be different due to holidays, etc. The results are unchanged. Results for any of these robustness checks can be provided by request.

race in the manner discussed thus far. Due to this contrary finding, the next section further investigates endogeneity by abandoning the assumption that the automated cameras are a valid comparison, and instead, following a procedure similar to Grogger and Ridgeway (2006) where the population depends on daylight, but only utilizes one ticketing source at a time.

VI. Investigating endogeneity by utilizing daylight savings time

Next, I explore a slightly different approach to support the previous analysis. Grogger and Ridgeway (2006) estimate the population at risk of being stopped by police by comparing the racial distribution of drivers stopped at night to the distribution stopped during the day. This analysis relies on a concept they call the "veil of darkness." During the daytime, when race is visible, it is possible that police use the race of the driver as a determinant of whether or not to stop a car. At night it is unlikely that police can distinguish between different races, and therefore presumably make traffic stops based on actual offenses without regard to the driver's race. A direct comparison of the two distributions assumes that driving patterns, driving behavior, and police exposure are the same during the day and night, but by exploiting information from daylight savings time, they are able to control for driving patterns while still comparing tickets issued in the dark to those issued when the sun is up. Individuals' work schedules as well as police patrol schedules, differ by time of day and not by darkness. They find no evidence of racial profiling.

Following the logic of 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 have no driver visibility and cannot observe 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. All other controls are the same as in Table 3.

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 4 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 look only at tickets issued during daylight hours, when drivers are visible to police, it is obvious that ticketing behavior is different between police and automated sources. 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.[25] Recall that only tickets issued between

Table 4. 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]

Note: 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.

[25] 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 to a lesser extent.

6:00 AM and 7:59 AM and 5:00 PM and 6:59 PM are included in these estimates, 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 5, 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 6. Since automated

Table 5. Probit marginal effects: investigating the effect of daylight on police-issued tickets

Variable	African-American	Female
Daylight	.110*	.297**
	(.057)	(.124)
70506	-.180**	.134**
	(.040)	(.038)
70508	-.161**	.049
	(.040)	(.177)
HalfMonth 1	-.032	.045
	(.026)	(.036)
Rush Hour	.019	-.334
	(.210)	(.188)
LegalSpeed	.008**	.014*
	(.003)	(.008)
11-15 Miles Over	-.120**	.137
	(.039)	(.110)
More than 16 Miles Over	-.124	.161
	(.100)	(.138)
Weekday	-.130**	-
	(.049)	
N	266	265
ln L	-151.60	-175.09
BIC	314.35	361.33

Note: 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. Weekday for column II drops out since 3 observations were weekend tickets issued to women.

sources are objective there should be no difference in ticketing by race or gender merely because it is light as opposed to dark.[26]

The coefficient on *Daylight Visibility* is significant when considering police issued tickets, where ticketed drivers are more likely women (African-American), but there is no difference for automated sources. These findings coincide 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.

Table 6. Probit marginal effects: investigating the effect of daylight on automated-issued tickets

Variable	African-American	Female
Daylight	-.117	-.005
	(.145)	(.167)
70503	-.126**	.366**
	(.019)	(.018)
70506	-.170**	.274**
	(.029)	(.014)
70508	-.085	.495**
	(.052)	(.032)
HalfMonth 1	.044	.249**
	(.061)	(.077)
Rush Hour	-	.173
		(.356)
LegalSpeed	.002	-.013**
	(.003)	(.005)
11-15 Miles Over	.055	-.134**
	(.095)	(.048)
Weekday	-.011	-.093
	(.172)	(.127)
N	119	126
ln L	-68.04	-69.68
BIC	150.42	153.87

Note:The reported values are the marginal effects, estimated using individual-level tickets. Robust standard errors, clustered by zip code, are in parentheses. * denotes significance at a 10% level, and ** denotes significance at a 5% level. Only one ticket over 16, which was excluded from the sample for estimation.

[26] This analysis can be performed by zip code, but the sample size for some are too small to estimate. However, those where the sample is large enough produce similar results as when aggregated. These results are available upon request.

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 is significantly higher if the ticket was issued by a police officer versus an automated source. The results are mixed when considering race of a driver, suggesting non-systematic consideration of race in issuing speeding tickets, though some evidence still exists that race is not completely ignored. Conversely, the results imply that gender plays an important role when police decide whether to ticket a speeding driver. Even when controlling for additional factors like type of road where the ticket is issued, the results remain the same.

This rich dataset has not been used previously to study police behavior and differential treatment in receiving speeding tickets based on gender and race.[27] 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. Another problem in some existing literature is the use of police reported stops, where not all stops are actually recorded. However, the present data set includes all speeding tickets given during the sample time period. 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. 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.

I employ numerous techniques to illustrate that the automated sources do provide a valid population measure to speeders observed by police. Suggestive evidence using maps of Lafayette and extensive regression controls for location and driver

[27] 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.

behaviors, as well as manipulation of daylight visibility all provide the same conclusion: police officers ticket a larger proportion of women than automated sources. In regressions explicitly controlling for type of road (city vs. neighborhood), drivers' race is not significant, however, in all other specifications it is. The gender effect is larger, and more consistent throughout all methods.

Despite the fact that I 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,[28] this would constitute a regressive tax based on unequal treatment. Further research is necessary to investigate whether differential contesting rates (or likelihood of future offenses, etc.) 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, but in any case, the welfare implications are similar.

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