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# The Policy of Enforcement: Red Light Cameras and Racial Profiling

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**Abstract**

We explore the question of whether some of the often conflicting evidence of racial profiling can be cleared up using red light camera observations to measure racial disparities in traffic violations. Using data from cameras at intersections matched to census data, we find that although citations from the red light cameras are issued to a disproportionate number of minorities based on the racial composition of the surrounding location, the racial composition of the violator is consistent with the racial composition of the block group in which they reside. Our study indicates that red light cameras may have a present and future role in assisting public policy makers on issues of racial profiling thresholds.

**Keywords**

red light cameras, traffic law enforcement, racial profiling

## Introduction and Background

Despite the increasing fervor of popular media and federal and state policy makers' attention to the issue,[1] the sources and evidence of racial profiling in traffic law enforcement remain largely unknown and, until recently, under-studied (Novak, 2004; Ward, 2002). The lack of empirical information about

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racial profiling has been costly, resulting in "an onslaught of civil lawsuits, legislatively or court-ordered data collection efforts, and voluntary data collection efforts on the part of police to explore racially biased practices" (Novak, 2004, pp. 65–66). Some of the deficit in empirical evidence is due to racial profiling as a relatively recent phenomenon; the term was rarely heard prior to 1995.

Most of the limited research on racial profiling has found "to varying degrees that police disproportionately stop people of color for traffic violations relative to population composition and treat minorities differently than whites during encounters, e.g. citations, arrests, length of time persons are stopped and searches of persons and their possessions" (Novak, 2004, p. 66). Rojek, Rosenfeld, and Decker (2004) suggest common findings of these studies, including their own, regarding racial disparities in traffic law enforcement; there are small but significant differences in how persons from different racial groups are treated during traffic stops, and Blacks and Hispanics are more likely than Whites to experience police stops and sanctions including arrest. There are limitations to these studies; they are almost exclusively based on records in large city police departments or state-level police agencies, ignoring contextual effects of location or neighborhood of the traffic stop or citation (Novak, 2004; Rojek et al., 2004).

Until recently, traffic stops were seen as some of the least controversial and problematic aspects of policing (Ward, 2002). Red light running, a prevalent traffic stop by law enforcement, is an especially difficult problem. Porter et al. (2001) found that despite most drivers' knowledge of the dangers of running red lights, 20% of drivers report having run red lights during their last 10 intersections. Interventions such as red light cameras are encouraged, especially given the initial empirical studies that show that cameras at signalized intersections reduce violations by at least 40% (Retting & Ferguson, 2003).

Empirical studies of red light cameras and their effect on traffic infractions are in their infancy compared with research programs on racial profiling. Red light cameras in the United States are about 20 years old, first implemented in New York City in 1993 (Ruby & Hobeika, 2003). While not shown to be less costly than traffic stops by law enforcement officers, red light cameras may be cost effective, given the number of deaths and injuries associated with red light running. Further, red light cameras seem to resolve some of the logistic and safety issues concerning catching red light runners. Traditional methods of red light running crackdown include strategic stationing of police officers at troublesome intersections, requiring the officer to run the red light or otherwise impede traffic flow to apprehend and cite the violators (Ruby & Hobeika, 2003).

We are not aware of any studies that show a relationship between race and red light camera citations. In other words, does the use of red light cameras mitigate racial disparities in traffic enforcement? Is it an answer to racial profiling concerns by explaining racial disparities in citations or violations? To answer these questions, our study examines red light running citations resulting from camera-tripping occurrences at 18 intersections. Due to the demographic makeup of residents, 76% are White; this area is especially prone to suggestions of racial profiling.

In this article, we provide a brief overview of the key literature on racial profiling and the sources of racial profiling. We address the limitations of prior empirical studies of racial profiling during police encounters with violators and suspected violators. We describe the unique contributions of data concerning camera-based citations to study this issue. Using the data collected, we examine the validity of prior studies that suggest that a contributing factor to minorities being stopped more than Whites at certain intersections for certain traffic violations may be explained by where the violators drive as opposed to where they live. We present our findings concerning racial disparities in red light running citations resulting from tripping a camera at a signalized intersection. Finally, we explore possible reasons for the differences between findings in other studies of racial disparities in traffic law enforcement by police officers and our findings of no racial disparities in red light running citations using red light cameras.

## Defining and Explaining Racial Profiling

Racial profiling is defined by the General Accounting Office (GAO, 2000) as a situation where race is used by the police as a factor in deciding whether to make a traffic stop. Others have refined this definition to suggest that racial profiling only occurs when race is the sole, or at the very least primary, reason influencing a police officer's decision to initiate the traffic stop (Engel, Calnon, & Bernard, 2002; Fridell, 2005; Lange, Johnson, & Voas, 2005; McMahon & Kraus, 2005). Racial profiling should be relatively easy to demonstrate—if factors other than race do a better job of explaining the enforcement activities of police authorities, then the claim of racial profiling is weak (Novak, 2004).

What may be more difficult to determine are the sources of disparities that Harcourt, Novak, Rojek, and others have tentatively identified as bigoted police officers, cognitive stereotyping, or contextual discrimination related to the premise that minorities are more likely than Whites to commit drug offenses or have outstanding arrest warrants, incentives for officers to stop certain types of offenders who may indirectly share racial characteristics and differential driving practices and behaviors (Harcourt, 2004; Lange, Johnson, & Voas, 2005; Novak, 2004; Rojek et al., 2004).

An especially interesting aspect of the explanation of the sources of racial disparities in traffic enforcement concerns explanations of differential risk-taking driving behavior between minorities and Whites. There are studies that have conflicting results on racially disparate driving behavior, including Lamberth's frequently cited 1996 Report to the American Civil Liberties Union, which found that Blacks did not differ from Whites in speeding behavior on Maryland highways (Ward, 2002) and Lange, Blackman, and Johnson's (2001) often-cited report of speeding on the New Jersey Turnpike, which found that Blacks are more likely to speed than Whites and at especially high rates of speed. The reason for the differences in findings may be the multiple and complex factors that seems to encourage high-risk behaviors (including red light running) in minorities that result in death and injury (Porter & England, 2000; Yee et al., 1995).

### *The History of Racial Profiling as a Policy Challenge*

Racial profiling (or race-based hostility and bias by law enforcement officers) finds its roots in the complex political context of urban policing, a multifaceted task under the best of circumstances. "Poverty, social isolation and economic stresses within urban core cities made the closest representatives of 'the system', the police, a target for the rage of the community" (O'Reilly, 2002, p. 106). On the other hand, urban areas are the primary drug trafficking marketplace, a condition that is considered as a societal danger calling for additional or at least differential law enforcement measures. In the late 1990s, a delicate balance between equitable and courteous traffic enforcement and aggressive interception of drugs and other contraband evolved—the controversy has continued to this day (O'Reilly, 2002). Tyler and Wakslak (2004) confirm this phenomenon, reporting that their results from interviews of 521 residents of two California cities support their findings that judgments about whether racial profiling occurs in a community is related to the level of support for and trust in police by the community.

Novak (2004) provides a slightly different history of the progression of the concept known as racial profiling that has generated academic and media attention:

> The discovery of racial profiling may be traced back to a 1993 civil case involving Robert L. Wilkins. The plaintiff, a black attorney, alleged that Maryland State Police stopped him for no other reason beyond his ethnicity. These allegations led to a consent decree and resulted in research conducted by John Lamberth. In his analysis of traffic and enforcement patterns on Maryland highways, he discovered that although blacks made up 17.5% of all traffic violators, they made up approximately 35% of those whom the police did stop. Furthermore, he reported 72.9% of those individuals who were searched by the police were black. Lamberth later conducted similar research in New Jersey as part of a criminal prosecution and found similar results reported in the (1996 case) State of New Jersey v. Soto . . . As a result of these earlier inquires, police departments began voluntarily auditing their own enforcement activities to determine if similar practices were occurring in their own jurisdictions. (p. 70)

## The State of Empirical Research on Racial Profiling

Despite the numerous law enforcement internal investigations and media probes of racial profiling, there are significant academic voids in empirical research (GAO, 2000). Most of the limited scholarly research on racial profiling in traffic law enforcement uses data from big cities with no differentiation for neighborhoods or the residence of the violator that are surely more racially homogeneous than a city or state unit of analysis (Novak, 2004;Rojek et al., 2004; Ward, 2002). Few of these examinations (including internal audits by police departments as a result of legal consent decrees or pressure by special interest groups) of racial profiling that have been popularized in the media have been subjected to traditional peer review or disseminated in scholarly or academic journals (Petrocelli, Piquero, & Smith, 2003). Even fewer studies employ multivariate analytical techniques (McMahon & Kraus, 2005). This is not to suggest that the studies to date have not been helpful. It is our contention that comparing frequencies of traffic stops by law enforcement officers by race of suspected offender is not as effective or telling for policy development as more sophisticated statistical modeling of traffic stop and citation data. This is due to the lack of consideration given to the heterogeneity of race and geographic locations, including looking at where violators live and not just where they commit the offense (Novak, 2004; Ward, 2002). Novak (2004) points out the greatest problem with the historically simplified approach—the lack of consideration of geography.

There are exceptions to this narrowly focused view of racial profiling research; these include a study conducted by Zingraff et al. in 2000. In their examination of highway patrol districts, they created a denominator using a weighted estimation of how many drivers on the road were from the other districts in the state (Zingraff et al., 2000). Rojek et al. (2004) had similar findings—that racial profiling cannot be asserted if there are a disproportionate number of stops of non-White drivers based of the racial makeup of the residential population of the area of the traffic stop. Others, such as Alpert, Smith, and Dunham (2004), begin to address the narrowly focused research by implementing multiple data collection processes into benchmarks. In Alpert et al., the objective is the use of high-volume intersection observational data on race and known not-at-fault crash data for the same intersection as a mechanism for establishing an estimate of the racial composition of the driving population within the intersections analyzed. This step advances the literature through the combinational use of observation and historical crash information to allow a look at the population characteristics of those using the intersection. This study acknowledges a new thought in racial composition and traffic violation actions. Tillyer, Engel, and Cherkauskas (2010) summarize the changing data collection efforts in law enforcement to address issues of racial profiling. They note a variety of benchmarks identifying the strengths and weaknesses of each type or grouping of benchmarks.

Our study contributes to the changing approaches to driver geographic heterogeneity—nonresidents being stopped in a jurisdiction and the racial composition of nonresident drivers likely being different than that of resident drivers—into consideration when evaluating racial disparities in traffic enforcement. We suggest that some of the costly time and effort spent by state and federal policy makers and law enforcement agencies responding to charges of racial profiling could be saved or better targeted if it is demonstrated that racial profiling is less a factor of law enforcement culture and more a factor of the differences in driving population from the local population. These responses have included both policy changes and expensive private evaluations to determine the extent of profiling behavior by law enforcement (Ward, 2002).

### *Enter the Neutral Source of Citations—The Red Light Camera*

The benefits of having red light cameras, including reduction in injury crashes, are apparently numerous and, as of 2002, at least 50 communities in the United States have adopted the enforcement technology (Retting & Kyrychenko, 2002). Several studies show that cameras are not without limitations and potential problems such as increased rear-end crashes and spillovers that result in crashes or violations at nearby but not camera-installed intersections (Chinnock, 2005; Retting & Ferguson, 2003). One of the benefits of red light cameras is they raise public awareness by notifying potential violators that enforcement is not only in effect, it is fair and equitable (Naso & Parker, 2004; Ruby & Hobeika, 2003). This awareness-raising factor is key, given that racial profiling is two sided involving both potential violators and potential racial profilers (Holbert & Rose, 2006). The process of informing potential violators of the risk of enforcement serves to level the playing field and to encourage constructive public dialog that is critical to effective policing (Fridell, 2005).

There are no studies to our knowledge that address the benefits of red light cameras as a means for mitigating racial profiling in law enforcement. We find this surprising, given the numerous studies on the challenges of data collection on racial profiling, including limited resources and previously unsupported assumptions that have guided data collection and analysis to date (Engel, Calnon, & Bernard, 2002; Ramirez, McDevitt, & Farrell, 2000; Smith & Alpert, 2002). Making an objective, scientific assessment regarding whether officers in a particular agency are engaged in racial profiling using data on stopping behaviors requires some subjective judgment of motives (Holbert & Rose, 2006). Rodriguez (2001) describes how typical data collection on stopping behavior and incidence limits the ability to analyze a key aspect of effective law enforcement: police discretion.

## Methodology

We explore whether red light cameras show sociodemographic characteristics of violators that are different from the sociodemographic characteristics of the population within the jurisdiction. The original data file from law enforcement contained 8,383 records. These records contain information on the intersection where the violation occurred; the automobile involved; and the gender, race, and address of the registered owner of the vehicle. Violations were spread across 18 intersections contained in the data file. All intersections are marked with signage indicating the presence of red light violation cameras. Cameras only produce photos in cases where the vehicle crosses the stop bar after the beginning of the red phase and continues through the intersection during the red phase of the signal. The civil fine for violations is about \$70.00. The citation for the violation and the civil penalty are not linked to the driver's license, and thus the effect is financial only.

Procedurally, violator license tags are matched to state vehicle registration/driver's license information to determine the likely driver of the automobile. Citations are mailed to the registered owner's current address and appeal options are listed on the citation. This database contained only violations matched to in-state violators that were not appealed by the recipient of the citation.

Street data information from the Census 2000 TIGER/Line files was utilized to match the violator's address to map locations. Using ESRI ArcMap 8.3 with the Census 2000 road files resulted in 7,865 valid matched records statewide (93.8% of cases). Restricting the sample of citations to where the cameras are located and the surrounding counties further limited the sample to 7,756 citation records. This total represents about 92.5% of the original number of records received from law enforcement.

Address points mapped to map locations were matched with census block group definitions from the Census 2000 TIGER/Line file block group boundaries using ESRI ArcMap 8.3. Designating the block group as the matching unit allows matching between Census 2000 summary file values calculated at the block group level. Although population, race, and gender values are available at the block level, other variables of interest to the analysis are only provided by the Census Bureau via sampling at the block group level. These variables include information on education levels, income, and vehicles per household that are only revealed at the block group level.

After matching address points to block groups, individual citation data were aggregated to the block group level. This aggregation process generated one observation per block group with each block group containing a value representing its total number of citations (violations). Census 2000 Summary File 1 was used to source information on population, racial characteristics, gender distribution, and number of households within block groups. Census 2000 Summary File 3 was used to source information on median income, educational attainment, and aggregate number of vehicles within block groups. Information on the aggregate number of vehicles combined with number of households allowed the generation of a vehicle per household variable. In addition, the block groups were assigned a distance value based on their distances in miles from the mean camera coordinates calculated from the 18 intersections where cameras were located. This measurement is based on Euclidean distance from the mean camera location to the nearest point of each block group. The final data file used for analysis contains 2,882 records, the total number of block groups contained in counties of interest.

It is important to note that any study using race as an explanatory variable is subject to scrutiny concerning the definitions of race and the challenges of unpacking the heterogeneity of race such as the differences between Hispanic and non-Hispanic Whites. Certainly, our preference would be to have as finite definitions of racial groups as possible; however, we are limited by the Census data available at the block group level.

## Descriptive Results

To explore the sociodemographic characteristics of red light violators caught by the neutral observer—the red light camera—we initially offer the racial profile of those caught by the camera. As is shown in Table 1, the racial profile of those caught by the camera running the red light differs from the population characteristics of the county with the red light cameras. This difference is quite apparent in the descriptive profile. To develop this point of difference, consider the following description. The cameras are located in a county composed of about 75% White and 15% Black in the general population. This composition differs from what law enforcement in the county with cameras sees: a racial composition of red light violators that is about 62% White and 30% Black. This finding is further amplified if we assume the police only observe residents of the county. County residents who are caught running red lights by the camera are composed of about 71% White and 20% Black.

If we assume that red light violators are similar to any other traffic violators, one would assume that law enforcement in the county with cameras would have a disproportionate number of car stops for traffic violations based on the racial composition of the violator and not the racial composition of the county. We should see that the violator composition of law enforcement traffic stops for the county with cameras at about 62% White and about 30% Black. This is a different racial composition than the general populace, although this proportion would not indicate racial profiling by law enforcement because the racial composition mirrors that observed by the camera.

Although the descriptive composition of the counties provides insight into the possible difference found between traffic stops and the racial composition of the county in which the violation occurred, our analysis explores the residence of the violator. We find support for violators' racial composition differing from the area in which they committed the violation, but we are also interested in the racial composition of the area where the violator resides. The following question arises: Although the violator differs from the location demographics of the area

**Table 1.** Descriptive Data for the Eight-County Area.

| Geographic area | Population | Population percent White | Red light violator percent White | Population percent Black | Red light violator percent Black |
|---|---|---|---|---|---|
| Total area | 3,433,358 | 65.37 | 61.80 | 26.34 | 30.17 |
| County 1 | 481,371 | 82.64 | 79.13 | 13.80 | 15.02 |
| County 2 | 743,529 | 75.47 | 65.63 | 20.39 | 25.92 |
| County 3 | 149,795 | 96.40 | 95.99 | 2.29 | 2.72 |
| County 4 | 192,401 | 90.66 | 90.65 | 6.46 | 6.89 |
| Camera County | 242,407 | 75.99 | 71.36 | 14.74 | 19.80 |
| County 6 | 843,224 | 67.09 | 66.19 | 15.68 | 19.72 |
| County 7 | 780,631 | 27.76 | 35.10 | 64.38 | 53.23 |
| County 8 | 641,600 | 32.10 | 37.63 | 65.30 | 60.61 |

of the violation, is the violator's racial composition different from that of the block groups in the area? Framed in a different light, is the racial composition of the violator's residence block group different from block groups in which no violations occurred? If so, do these differences affect the violation count for block groups? This addresses the literature that infers that the sociodemographic composition of an area with a high crime rate differs from an area with a low crime rate, assuming a correlation between crime and traffic violations. This allows us to posit the hypothesis that block groups with red light violators will not differ in racial composition from those block groups without red light violations in the area of study.

## Empirical Evaluation

To address the implication of block group composition on red light violators, we offer a regression model focusing on racial composition of the block group while controlling for factors that should affect driving behavior. We list the variables and their descriptions in Table 2. One of the control variables requires further explanation. The control for male population above the 99th percentile, identified as High Male Pop, controls for block groups in the counties that are contiguous to the county with red light cameras that have specific institutional characteristics such as a university and/or military base. These block groups confound the population distribution of males and females in a county. We control for these specific institutional characteristics with a dichotomous dummy variable indicating a block group with a high proportion of males within the contiguous counties. The 99th percentile is a block group with over 63% males.

**Table 2.** Description of Variables Used in Negative Binomial Regression Analysis.

| | Description |
|---|---|
| Dependent variable | |
| Violations | Count variable indicating the aggregate number of red light violations in a block group |
| Independent variables | |
| Percent White | Percentage White in block group |
| Percent Asian | Percentage Asian in block group |
| Percent American Indian | Percentage American Indian in block group |
| Percent Other | Percentage Other in block group |
| Household size | Mean household size in block group |
| Vehicles per household | Mean number of vehicles in household in block group |
| Median household income | Median household income in block group |
| Natural log of distance | Natural log of distance from red light cameras |
| High male population | Dummy variable indicating block group with a male population over the 99$^{th}$ percentile |
| Population | Total population of the block group self identifying as one race |
| Working poor | Percentage of households with income between 101% and 200% of federal poverty level for Census 2002 |
| Poverty | Percentage of households at or below the federal poverty level for Census 2002, average family of three |
| Camera | Dummy variable indicating the county with red light cameras |
| Percent college | Percentage of college-educated individuals in block group |
| Percent male over 18 | Percentage of males over 18 in block group |

The evaluation uses the Negative Binomial Regression Model (NBRM). The NBRM allows for a maximum likelihood of correction for overdispersion in the model, avoiding the lack of efficiency obtained with overdispersion in the Poisson Regression Model estimates. NBRM replaces the conditional mean of a Poisson regression with the random variable mean. This incorporates an error term into the mean that accounts for the combined effects of unobserved variables that have been omitted from the model or as another source of pure randomness. By using the NBRM, the model addresses the notion that both variation in the independent variables and unobserved heterogeneity produce the variation in the mean.

To begin the analysis, the data in Table 3 present the descriptive statistics for the 2,882 block groups under investigation. The average block group population is about 1,412 with a racial composition of about 58% White, 35% Black, and

**Table 3.** Descriptive Statistics for Variables Used in Negative Binomial Regression Analysis.

| | Mean | Median | *SD* |
|---|---|---|---|
| Red light citations | 2.66 | 1.00 | 7.86 |
| High male population | 0.94 | 0.00 | [a] |
| Population | 1411.56 | 1216.00 | 812.01 |
| Percent White | 58.17 | 68.75 | 35.29 |
| Percent Asian | 4.09 | 1.85 | 5.47 |
| Percent American Indian | 0.30 | 0.21 | 0.35 |
| Percent Black | 35.38 | 18.57 | 36.11 |
| Percent Other | 2.04 | 0.63 | 4.32 |
| Household size | 2.66 | 2.70 | 0.47 |
| Vehicles per household | 1.52 | 1.59 | 0.60 |
| Median household income | 57,715 | 52,820 | 29,616 |
| Natural log of distance | 2.77 | 2.83 | 0.52 |
| Working poor | 10.62 | 0.00 | [a] |
| Poverty | 2.81 | 0.00 | [a] |
| Camera | 4.02 | 0.00 | [a] |
| Percent college | 24.48 | 21.80 | 16.15 |
| Percent male over 18 | 46.73 | 47.10 | 4.69 |

*Note.* $N = 2{,}882$ block groups. [a]Standard deviation has limited meaning due to nominal variable measurement.

4% Asian. Median household income in the average block group is $57,000. The average household in the block group has 2.66 individuals with about 1.5 vehicles. About 14% of the households within the block groups are considered working poor or in poverty.

Turning to the results of the NBRM, presented in Table 4, two outcomes are offered. The first outcome is the beta coefficient for the NBRM and its associated standard error. The beta is then converted into a percent change to allow for interpretation of the coefficient.

The empirical results provide support for the hypothesis that racial composition does not affect the number of violations in a block group. All racial composition variables lack statistical significance at the conventional level of .05. The effect of other sociodemographic characteristics, median household income and the size of the population, is statistically significant; however, the magnitude of their impact is very low. The two largest impacts are from the variables that measure availability of vehicles to the household and distance from the red light cameras. The magnitude of the number of vehicles available in the household indicates that an increase of one vehicle in the average household in the block

**Table 4.** Negative Binomial Regression Results of Block Groups.

| | β | *SE* | Percent Δ |
|---|---|---|---|
| High male population | −1.135 | 0.606 | −66.10 |
| Population | 0.001*** | 0.000 | 0.10 |
| Percent White | 0.172 | 0.093 | 19.60 |
| Percent Asian | 0.274 | 0.435 | 90.90 |
| Percent American Indian | −9.588 | 7.785 | −100.00 |
| Percent Other | −0.778 | 0.732 | −58.80 |
| Household size | −0.272** | 0.083 | −21.70 |
| Vehicles per household | 1.070*** | 0.099 | 184.20 |
| Median household income | 0.000*** | 0.000 | 0.00 |
| Natural log of distance | −0.371*** | 0.092 | −76.60 |
| Working poor | −0.401** | 0.129 | −58.70 |
| Poverty | −0.960** | 0.295 | −29.00 |
| Camera | 0.415 | 0.093 | 22.90 |
| Percent college | 0.485 | 0.266 | 47.60 |
| Percent male over 18 | −0.359 | 0.830 | −9.90 |
| Constant | 1.937 | 0.392 | |
| Alpha | 0.299 | 0.030 | |

*Note.* $N = 2{,}882$; $\chi^2 = 5315.76$, $p > .0000$; McFadden's adjusted $R^2$: .249.
$^{**}p < .01$. $^{***}p < .001$.

group increases the expected number of violations in the block group by 184%, holding all other variables constant.

The distance measure indicates that as we move away from the camera location, a rapid decrease in violations per block group occurs. The other three variables that are statistically significant include the average size of the household and two measures of poverty. Interpreting the effect of average household size, as the average size of the household increases by one individual, the expected count of violations in the block group would decline by about 22%. Finding no literature to use as grounding, we can only speculate about two potential explanations for this occurrence. The first is that the increase in the average household size is a child. We expect drivers with children to reduce their risk-taking behavior while driving. The second explanation is that learning is taking place and that the increase in the household size is mirrored by the occupants of the household providing information to the *new* occupant explaining the red light camera costs.

The two measures of socioeconomic influence are as follows: First, the block group is designated as working poor if the average household in the block group indicates income levels between 101% and 200% of the federal poverty level.

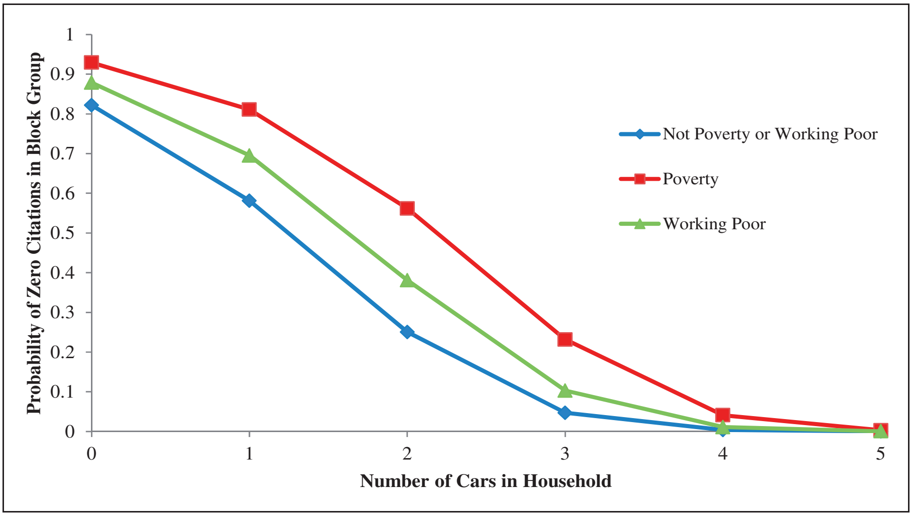


**Figure 1.** Probability of zero citations for a given number of cars in household.

Second, the block group is designated as poverty if the average household in the block group is at or below the federal poverty line. Both of these variables are negative, an indicator that since the red light violation is a civil financial penalty only, these two groups are aware of the financial costs and thus reduce their probability of risky behavior that has financial implications. As shown in Figure 1, the relationship between a block group having the probability of zero violations and the number of vehicles in the average household varies based on socioeconomic status. This is also seen in the magnitude of the percentage coefficients.

## Discussion and Policy Implications

The role of racial profiling and the measure of profiling behavior have traditionally focused on law enforcement personnel and the inference of profiling based on human factors. In this article, we have explored an alternative to the human factor issues of racial profiling by looking at profiling from the standpoint of an objective observer, the red light camera. What we have found is that, compared with the racial composition of the county, the red light camera observes a different racial makeup. This may be one of the influences in racial profiling if we assume that the camera and law enforcement observe the same phenomena. We then explored the racial composition of the block group in which the red light runner resides. We find that the racial composition of the block group does not influence the count of red light violators in that block group. We found some initial support for driving factors other than race, such as distance from the location of the violation and the accessibility to a vehicle, playing larger roles with respect to the number of violations in a block group. We readily admit that much more exploration is required before we are ready to contend that these driving factors explain red light running violations. It is important that we limit both our analysis and the recommendations. We support this thought with two reasons. First, due to data limitations, we are clearly lacking possible causal and explanatory variables. Second, our data are based on vehicle registration. To explore driving factors in more detail would require knowing the vehicle driver at the time the camera was triggered. We framed our argument not only on limited geography for the red light camera locations but also on limited geography of the contiguous counties that encompass the area where the cameras are located.

So, we are confronted with suggestions to offer policy makers. First, we have preliminary evidence that the racial composition of the county differs from the racial composition of the violators as identified by the camera. Second, we have some evidence that indicates, at the block group level, that racial composition does not affect the number of red light running violations. We suggest that the camera may provide a behavioral representation that may be used to mitigate some of the racial profiling rhetoric. At the same time, our limited data force us to take care in not overstating our results. The current literature indicates behavioral differences based on race with respect to traffic violations. We have not confirmed or refuted this premise, but we have found that violators captured by a red light camera do not vary significantly in terms of race from the profile of their block group of residence. This contrasts the role of race within block groups, indicating that the block group, not the racial composition of the block group, may be the measurement indicator for behaviors and actions. In policy, the assumption is that the racial composition of the block group is what matters; however, our research would indicate it is potentially the nature of the block group itself, not the variation in racial composition of the block group that is important.

Additionally, we found some evidence that would oppose the anecdotal statements that the poor are disproportionately affected by red light cameras. Anecdotal evidence and advocates for the poor suggest that the poor and working poor would be adversely affected as they are working during all shifts of the work week. We do not find evidence that the poor or working poor are adversely affected while controlling for other aspects of sociodemographic composition in our analysis. Our outcomes would lead to the interpretation that red light cameras are not policy barriers to those in poverty or near poverty. The cameras appear to be tools to assist traffic law enforcement without placing undue harm on workers regardless of their income strata. However, we note that the focus of this analysis is on racial profiling and not the effect of red light camera citations on the poor.

Our research would suggest that, in addition to using red light cameras to mitigate dangerous driving in certain intersections, it might be possible to use the cameras to address complaints of racial profiling behavior in certain neighborhoods or communities. This technology might be a timely and cost-effective supplement to internal and external audits or legal inquiries. Before proffering this as a policy solution, we would encourage research using longitudinal data and numerous comparative geographies. It may be that this technology is more effective in some contexts than in others. In addition, our research opens future research to explore the unbiased nature of red light cameras and the actions of law enforcement. A comparison, by race, of red light violators and those stopped and cited in the same geographical area is the next step to observe the implications of red light cameras and racial profiling. If the resulting action of law enforcement and that observed by the camera is similar, then this redefines the issue of racial profiling. If our results are supported by future research, then the resulting outcomes can lead policy makers to potentially undiscovered policies that assist in educating and thereby mitigating the issues of racial profiling.

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## Note

1. A LexisNexis search on *racial profiling* and *traffic* produced 655 major newspaper citations from 2001 to 2005 and 467 citations during the prior 5-year period. Further, there have been a number of legislative proposals addressing racial profiling and police abuse, including the Traffics Stops Statistics Study Act of 2001 (Title II of Senate Bill 19 of the 107th Congress).

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