Driving while black: do police pass the test?

Patrick L. Mason

Florida State University

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Summary

■ Biased policing against racial and ethnic minorities is an important public policy issue. Theoretical analysis and empirical results on this issue has been plagued by an assortment of problems which confront research on the nature and significance of police discrimination against social groups. This paper presents and applies a non-parametric test that is robust to a host of methodological difficulties. We theoretically and empirically contrast our non-parametric test with other tests that are prominent in the literature. Utilizing data provided by the Florida Highway Patrol, our empirical results strongly reject the null hypothesis that FHP troopers of different races do not engage in racially biased searches of stopped drivers. More particularly, there is evidence of police bias against African American male and Latino drivers by all officers and no evidence of police bias against white male drivers by any group of officers. ■

JEL classification: JEL K42, J15.
Key words: racial profiling, discrimination, evolutionary game.

* *Patrick L. Mason is Professor of Economics and Director at the African American Studies Program, the Florida State University.*

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American racial and ethnic minorities often claim they are subjected to racially biased traffic stops, searches, and enforcement actions. In particular, Latino and African American motorists have labeled this phenomenon "driving while brown" or "driving while black." But, the perception of illegitimate racial profiling as a widespread element of law enforcement is at odds with publicly announced policies of law enforcement agencies such as the Florida Highway Patrol (FHP, 2003). The FHP states that, "profiling is illegal, inconsistent with the principles of American policing, and an indefensible public protection strategy." Further, the official policy of the FHP states that both patrolmen who are found guilty of engaging in racial profiling and supervisory officers who found guilty of condoning, encouraging, or ignoring patterns of profiling will be subject to disciplinary actions. Indeed, the FHP requires that supervisors take proactive steps to prevent profiling.

Racial or ethnic bias in policing may occur because of the social preferences of individual officers or because of the organizational culture of police agencies. Or, racial and ethnic differences in policing outcomes may indicate efficient enforcement rather than biased policing. Conceivably, racial disparities in policing outcomes may occur because of differences in the behavioral characteristics of citizens. For instance, if African Americans and Latinos are more likely to engage in traffic violations or criminal behavior then we will observe that drivers of these social groups are more likely to be stopped and searched than drivers of other social groups.

Finally, whether or not a given racial and ethnic pattern of policing outcomes represents biased policing, efficient enforcement, or both

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may well depend upon what one considers the fundamental objective of policing agencies. For example, if maximizing the "hit" rate (the fraction of searched drivers who are actually guilty of a crime) is the objective of law enforcement then we might well observe identical marginal hit rates across all social groups. However, this pattern of policing outcomes may not be consistent with policing which seeks to maximize public safety (minimize criminal activity of drivers).

Similarly, policing which seeks to maintain social control might be intentionally discriminatory even as it is also efficient with respect to the goal of maintaining social control. Socially cohesive communities, it is argued, have the families and non-governmental institutions that are sufficient to establish anti-crime norms of behavior that strongly discourage criminal activity. Less cohesive communities do not have the resources to establish strong social control over potential crime behavior. Social control related policing then refers to policing that is putatively designed to prevent criminal activity and to install appropriate respect for (or fear of) law enforcement officers among individuals who reside in communities that the police believe do not have the social cohesion necessary to establish strong anti-crime norms of behavior (see Choongh, 1998).

The present study focuses on FHP searches of stopped drivers. Specifically, we wish to determine if empirical evidence is consistent with racially unbiased searches of stopped drivers by individual law enforcement officers. We use evolutionary game theory to construct a political economics model of policing where the costs of failed searches constrain police discretion. Further, these costs vary with the racial and ethnic identity of stopped drivers. We include data on trooper characteristics as a means of identifying differential policing. Non-parametric results associated with an outcomes test presented herein show that the empirical evidence is not consistent with the efficient enforcement hypothesis; instead, we find that the statistical evidence is consistent with racially biased searches by law enforcement officers. Whether or not a stopped driver is searched is a separate issue from the precise nature of the enforcement actions brought against the driver by the FHP. We do not explore here whether individual officers carry out racially or ethnically biased enforcement actions against searched and un-searched drivers, that is, whether or not a stopped driver is given a traffic citation, an equipment citation, charged with a crime, or receives no punitive action at all.[1] Nor do we explore whether racial and ethnic bias is a determinant of which drivers police elect to stop. Finally, this study does not attempt to distinguish among the possibly multiple causes of biased policing.

This paper is organized as follows. Section 1 provides a discussion of the literature. We focus on the problems associated with determining a comparative benchmark for empirical analyses of biased policing. Also, we discuss the incentives for police to engage in discriminatory behavior. Section 2 provides an evolutionary traffic search game, which establishes an outcomes test for assessing the presence of racially and ethnically biased policing. We argue that this test has greater power than similar tests proposed in the recent literature on racial profiling and traffic searches by police officers. Our empirical analysis is offered in section 3. Our results suggest that police engage in racially and ethnically biased policing, to the detriment of African American and Latino drivers. We conclude in section 4.

1. Literature review

1.1. Biased policing defined

According to the FHP, illegitimate profiling exists when "the vehicle occupant's race, ethnicity, gender, or economic status was the reason for initiating the traffic stop and/or subsequent search of the vehicle." Nevertheless, the FHP's definition of racial profiling is inadequate. Specifically, it is too limiting to say that profiling exists only when social group status is "the" reason for initiating a traffic stop or vehicle search. Such a definition wrongly suggests that if social group status is also used in combination with other legitimate factors then profiling does not exist. Simultaneously, the FHP definition is also too narrow because it does not include differential enforcement actions in its definition of racial profiling nor does the FHP definition include actions that Georges-Abeyie (1989, 1990a, p. 12) has labeled "petit apartheid." Specifically, Georges-Abeyie discusses several informal, punitively discriminatory, and discretionary police actions that may not appear in official statistics. Examples include verbal assaults, rough or brutal treatment, unnecessary stops, questions, and searches, a lack of civility faced for racial and ethnic group suspects/arrestees,

[1] See Close and Mason (2006) for an analysis of enforcement actions.

and judicial instructions to juries that are of a lower quality, clarity, and objectivity when an African American or Latino arrestee is on trial.

The National Organization of Black Law Enforcement Executives (NOBLE) and the Police Executive Research Forum (PERF) have offered definitions of racial profiling that are closer to economists' understanding of discrimination as a residual influence after taking into account those factors that legitimately influence an outcome of interest. Specifically, NOBLE states that biased policing exists when, "The act (intentional or unintentional) of applying or incorporating personal, societal or organizational biases and/or stereotypes in decision-making, police actions or the administration of justice (NOBLE, 2001, p. 4)." Similarly, PERF states that "Racially biased policing occurs when law enforcement inappropriately considers race and ethnicity when deciding with whom and how to intervene in an enforcement capacity (Fridell, et al., 2001)." In other words, if an individual officer's enforcement behavior is biased by personal racial, ethnic or gender prejudice or animus toward other-group motorists or favoritism toward own-group drivers, this constitutes abuse of police discretion.

1.2. Comparative benchmark

Establishing a comparative benchmark represents an important and difficult obstacle for determining whether racial and ethnic inequality in traffic stops represents biased policing (Zingraff et al., 2000; Fridell et al., 2001). For example, the US General Accounting Office Report 2000 indicates that because of methodological challenges, it cannot "determine whether the rate at which African-Americans or other minorities are stopped is disproportionate to the rate at which they commit violations that put them at risk of being stopped." (Fridell et al., 2001, p. 136) Initially, the question of establishing a comparative benchmark arose as a methodological issue to determine whether a particular ethnic or racial group is being stopped disproportionately (Ramirez et al., 2000; Harris, 2002). Ramirez et al. (2000, p. 53) describe two different types of benchmarks: those that are external to the traffic-stop data and those that may be generated from within the data set. External benchmarks are defined as estimates of the percentages of persons by racial and ethnic group who are at risk for being stopped on roads that are patrolled by the law enforcement agency. Fridell et al. (2001, p. 137) define external standards as "those based on existing data, such as census data, or on new data, such as that provided by observing vehicles on the road." Within-data benchmarks or internal standards are described by Fridell et al. (2001, p. 137) as "analogous to an early warning system." In this case, officers, units, districts, geographic areas or other groupings are matched and compared with one another to control for factors such as circumstances and context. Reliance on external standards developed from existing data, appears to be the norm for most jurisdictions. According to Fridell, et al., the utilization of census data, drivers license information, vehicle accident data, Uniform Crime Report (UCR) arrest data, and researcher observation have served as external standards for some studies. Depending on the context in which they are applied, each of these standards has unique benefits as well as limitations.

Among studies that wish to examine the issue of racial profiling of motorists, evidence of discrimination is determined according to whether the racial-ethnic composition of stopped drivers differs from the racial-ethnic composition of an appropriately defined comparison group (Ramirez et al., 2000). Suppose, for example, Latinos are 35 percent of stopped drivers, but 15 percent of the population in the enforcement area. We cannot therefore conclude that relative inequality in the ethnic composition of traffic stops represents discrimination. The ethnic composition of the population may be quite different from the ethnic composition of drivers, which may differ still from the ethnic composition of persons engaged in a traffic violation or illegal activity, which may differ according to the time or date officers are deployed in an area.

The present study focuses on trooper actions after the traffic stop, specifically whether or not a stopped driver is searched. Nevertheless, the external comparative benchmark issue reasserts itself via the question of whether or not the coefficients of regression equations are statistically biased because of the existence of unobserved variables. For example, if preferences for and indicators of guilt of criminal activity are stronger among Non-Hispanic whites this may be observed by officers but not included in the data available to analysts. Thus, if regression analysis shows that white drivers and Latino drivers are equally likely to be searched the analyst would draw the erroneous conclusion that the data is consistent with unbiased policing.

The internal comparative benchmark issue reasserts itself via the issue of whether or not troopers of alternative racial and ethnic groups observe drivers of the same racial and ethnic composition. For example, African American and white officers may be deployed in a fashion such that white officers observe a disproportionate number of African American drivers while African American officers observe a disproportionate number of white drivers. So, in this case, regression results will show a correlation between the probability of search and the officer-driver identity match: white officers are more likely to search black drivers and less likely to search white drivers, while African American officers are more likely to search white drivers and less likely to search African American drivers. Yet, in this instance, the statistical importance of the identity match of officers and drivers reflects only differences in the racial composition of drivers in the respective areas of deployment of officers—not biased policing.

1.3. Inframarginality problem

The so-called "inframarginality problem" represents an additional element of the comparative benchmark issue. Standard economic theory focuses on the treatment of the marginal unit of analysis, in this case, the marginal driver. Standard regression analysis however focuses on the treatment of the average unit of observation, the typical driver. The "marginal motorists" are the last individuals deemed sufficiently suspicious to stop and search, but marginal drivers are not identified in the dataset. Consider the "hit rate," the fraction of times searched drivers are found guilty of possessing contraband. Importantly, inequality of average hit rates does not necessarily imply inequality of marginal hit rates. The marginal driver is the theoretical benchmark, but the average driver is the statistical benchmark; hence, this is an additional reason that standard regression analysis designed to detect whether or not race has a statistically significant residual effect, and thereby reject the null hypothesis that the police do not engage in racial discrimination, may be plagued by the omitted variables problem.

1.4. An outcomes test for biased policing

An important insight of Knowles, Persico, and Todd (2001) (KPT, hereafter) is that if police agencies are solely concerned with maximizing the hit rate, then in equilibrium we will observe equal hit rates across racial groups. However, this equilibrium is also associated with statistical discrimination since search rates need not be equal across social groups. If hit rates are not equal police may arbitrage the difference across racial groups so as to maximize the overall hit rate. As police increase their searches of high crime groups, drivers in those groups respond by decreasing their criminal involvement. As police decrease their searches of low crime groups, drivers in those groups respond by increasing their criminal involvement. Police will continue to reallocate their searches across social groups until the hit rates of both groups are equal. At equilibrium, equality of hit rates implies that the social group with the higher (lower) criminal propensity will have the higher (lower) search rate.

Let $\gamma(r, R)$ equal the search rate of race $r = \{a, l, w\}$ motorists by race $R = \{A, L, W\}$ officers and allow $\chi(r, R)$ to be a similarly defined hit rate, where the racial-ethnic groups are African Americans (a, A), Latinos (l, L) and whites (w, W). Although KPT presents the original statement, Persico and Todd (2005) present a stronger theorem of the empirical outcomes we should observe when biased policing is not present.

> "In any equilibrium, the hit rate is the same across all subgroups within a race. If the police are unbiased, the hit rate is the same across races, too. If the police are biased against race r, the hit rate is lower in race r than in the other race" (Persico and Todd, 2005, p.13).

It is important to note that the Persico and Todd efficient enforcement theorem assumes that drivers are heterogeneous in their characteristics and that officers are heterogeneous (not monolithic) with respect to the benefits and costs associated with police search activity.

KPT propose an extraordinarily simple outcomes test: divide the data into alternative social groups and compare hit rates. If the difference is statistically significant police are discriminating against the group with the lower hit rate. With KPT, we do not have to worry about whether our regression results suffer from omitted variable bias nor whether or not we are observing the marginal driver. Drivers from the group with higher criminality will have higher search rates, but the average hit rate for all groups will be equal. The KPT model predicts that all motorists of a given race, if they are searched at all, will carry contraband with an equal probability regardless of the other observable characteristics of the motorist. Hence, the comparative benchmark issues are not relevant.[2]

[2] Persico (2002) has shown that under these conditions, there is no tradeoff between police efficiency and egalitarian provision of civil liberties across racial

As an example of how to apply the KPT test, suppose that white drivers have a higher preference for crime than Latinos and neither white nor Latino officers are ethnically biased. For Latino-white bivariate comparisons, the KPT efficient enforcement theorem suggests that we should observe

$$\gamma(w,W) = \gamma(w,L) > \gamma(l,W) = \gamma(l,L), \text{ and} \qquad (\text{KPT, i})$$

$$\chi(w,W) = \chi(w,L) > \chi(l,W) = \chi(l,L). \qquad (\text{KPT, ii})$$

If the KPT conditions hold then we cannot reject the null hypothesis of efficient enforcement (that is, no discrimination) even though whites in this instance are searched at a higher rate.

Following the empirical work of Close and Mason (2002) and the practice of others within the literature on biased policing, Anwar and Fang (2006) (AF, hereafter) also argue that statistical discrimination by police agencies may occur when race helps predict whether a driver is carrying contraband (Bjerk, 2004; Dharmapala and Ross, 2004).[3] However, AF argue that if the signal on a driver's guilt is endogenous, KPT's model will not eliminate the inframarginality problem. Assume that θ^* is the threshold guilt signal. If so, all stopped drivers who emit a signal $\theta > \theta^*$ will be searched by the police. By an endogenous guilt signal, AF mean that stopped drivers who are actually guilty of a crime are more likely than non-criminal drivers to emit $\theta > \theta^*$.

AF then provide the following proposition for African American and white police officers and drivers.

> *If neither race-A nor race-W of police officers exhibit racial prejudice, then neither the rankings of $\gamma(r, A)$ and $\gamma(r, W)$ nor the rankings of average search success rates $\chi(r, A)$ and of $\chi(r, W)$ depends on $r \in \{a, w\}$. Moreover, for*

groups. See also Myers (2002) for a detailed analysis of the public policy implications of any tradeoff between police efficiency and civil rights equity with respect to racial profiling.

[3] See Close and Mason (2007) for greater detail on the specifics of Bjerk, Dharmapala and Ross, and other critics of KPT.

any r, the ranking of γ(r, A) and γ(r, W) should be the exact opposite of the ranking of χ(r, A) and of χ(r, W).[4]

With endogenous guilt signals, according to AF, we are left with examining only the rank-order of search rates and hit rates. Suppose white officers search more than African American and Latino officers. AF conclude that the data do not allow them to reject the null hypothesis of no discrimination if the following rank-order conditions hold:

$$\gamma(a,A)<\gamma(a,W) \text{ and } \gamma(w,A)<\gamma(w,W), \text{ and} \qquad (\mathrm{AF.i})$$

$$\chi(a,A)>\chi(a,W) \text{ and } \chi(w,A)>\chi(w,W). \qquad (\mathrm{AF.ii})$$

The AF test has rather limited power to detect discrimination. For example, even if both (AF.i) and (AF.ii) are true, the AF test will not detect discrimination under at least two conditions: 1) both minority and white officers discriminate against minority drivers, but white officers are more discriminatory; and, 2) minority and white officer search differentials are "too large" relative to minority and white hit rate differentials. As such, even if the rank-order of search rates and hit rates are consistent with the AF test requirements, the strongest claim that we may make is that the data do reject the null hypothesis of efficient enforcement. Of course, this is a very weak claim since it is also consistent with the alternative hypothesis that discrimination exists.

We present below a more powerful test. Further, we apply this test to the re-weighted FHP data constructed by AF. Our test reaches more definitive conclusions and we overturn the central conclusion of the AF study, i.e., we show that whether we use re-weighted data (as does AF) or completely raw data (we do here) the data reject the null hypothesis of efficient enforcement.

1.5. Incentives to discriminate

Policing is necessarily a highly discretionary and decentralized activity, which takes place in a market structure that is not characterized by the

[4] The notation of this proposition has been altered to fit the notation of this paper; otherwise, this is a direct quote from Anwar and Fang.

competitive pursuit of profit (Benson, 2003; Klein, 1979; Blomberg et al., 2002). Social scientists may disagree over whether the pursuit of profit by firms abets or ameliorates equality of opportunity, but there is near uniform agreement that unrestricted monopolies allow individuals with discriminatory preferences to indulge their racial beliefs without the disciplinary effect of market competition (Becker, 1957; Mason, 1999). Accordingly, even if executive policy within the FHP does not condone discriminatory behavior, implementation impediments (for example, individual trooper racial/ethnic stereotypes) combined with the high level of trooper discretion required for effective law enforcement may generate persistently biased policing. Moreover, the design and implementation of policies concerned with issues other than racial profiling and that are seemingly race-neutral, such as the much publicized "war on drugs," may have putatively unintended collateral consequences. Racially disparate outcomes in traffic enforcement searches may be one of these consequences.

Many scholars believe police abuse their discretionary authority by excessively stopping, searching, and charging African Americans and Latinos (Harris, 1999a,b).[5] For example, enforcing social discipline may require presumptive detention or search of some persons who are not current law breakers (Choongh, 1998). Choongh demonstrates that police sometime detain individuals that they have no intention of charging with an offense. Police engage in this sort of behavior because they are interested in subordinating sections of society viewed as anti-police or excessively criminal, rather than because they are immediately interested in criminal law enforcement. So, all stopped or searched drivers are not suspects; some drivers—detainees—may be stopped and searched for purposes of social control. The discretion awarded to individual officers on the street and to police agencies at the police station allows them to pursue an agenda of social control along with an agenda of criminal apprehension. The social control hypothesis suggests a higher ratio of detainees to suspects among targeted demographic groups. In our case, the social control hypothesis implies drivers in counties with large African American, Latino, and poor populations will face greater search intensity (and suspicion)—

[5] The Leadership Conference on Civil Rights (2003) has argued that police abuse of discretion proceeds from two (false) assumptions: "(1) blacks and Hispanics commit most crimes, and (2) most blacks and Hispanics commit crimes (p. 10)."

given the county's crime rate and other factors that might reasonably affect the probability that a driver is searched.[6]

Choongh's social control hypothesis is in agreement with some recent empirical findings. Donohue and Levitt (2001) show that increases in the minority composition of a city's police force increases the arrests of whites but has little impact on the arrests of nonwhites. Similarly, increases in the fraction of white officers lead to increases in the number of arrests of nonwhites but has no effect on the number of white arrests. Meehan and Ponder (2002) report that African American motorists stopped and searched in neighborhoods with higher fractions of white residents are less likely to have contraband than white motorists stopped in these same neighborhoods; yet, African American motorists are burdened with disproportionate surveillance and stopping by police in neighborhoods with a higher fraction of white residents.

Gordon (1971) establishes that policing is a political process that is regulated by a rational economic calculus that includes the political power of social groups. Citizens monitor policing activity and use their collective power to make adjustments in police practice. A straightforward application of Gordon's perspective suggests that the political economic power of citizens to impose costs on police for engaging in unnecessary or excessive searching varies according to several factors: an individual's access to public officials with regulatory authority over police, information regarding police oversight and citizen rights, ability to afford competent legal council, discretionary time to carry-out and persist with a complaint against police, belief that legal system will support citizens who make accusations against police, etc.. These factors vary across individuals and broad social groups. Racial and ethnic minorities in Florida have substantially less political, economic, and social power than whites (Button et al., 1998; Joint Center for Political and Economic Studies, 2003). Accordingly, troopers may have individual incentives to use their discretionary powers to search racial and ethnic minorities at a higher rate than otherwise identical whites.

Finally, our analysis of policing behavior should incorporate some of the recent theoretical implications of the economics of identity. In

[6] In a similar vein, Blalock (1967) argues that some police officers believe racial and ethnic minorities represent a social threat. The greater the perception of social threat, the more likely a police officer will use his discretionary authority to engage in racial profiling (Cureton, 2001).

particularly, Darity, Mason, and Stewart (2006) show that persistent antagonistic intergroup relations combined with intragroup altruism are elements of individual identity construction in a racialized society. If we apply this perspective to policing, the racial-ethnic identity match of officers and drivers may affect policing practice. Moreover, the relationship between the racial-ethnic identity match officers and drivers may vary according to the ecology of the traffic stop, viz., whether the stop occurs in a predominantly African American, Latino, or white area.

1.6. Summary

Biased searches of stopped drivers exists when officers inappropriately use race to determine whether a stopped driver should be searched. Establishing a comparative benchmark has been one of the difficulties of empirical tests of biased policing. The comparative benchmark problems has several dimensions: 1) the inframarginality problem, that is, distinguishing between police treatment of the average versus the marginal driver, 2) determining whether the racial composition of observed and stopped drivers is the same as the racial composition of drivers engaged in criminal activities, and 3) possible omitted variable bias in regression models. KPT developed a non-parametric outcomes test which purportedly evades the issues associated with the comparative benchmark problem. Assuming that police seek to maximize the hit rate, KPT show that in equilibrium we will observe statistical discrimination with unequal search rates (varying directly with the differential criminality of social groups) but equal hit rates, within and across social groups. However, among other issues, if stopped drivers who are actually guilty of a crime are more likely than non-criminal drivers to emit $\theta > \theta^*$ then the KPT test must be revised.[7]

It may also be the case that police do not seek to maximize the hit rate. Instead, they may seek to maximize public safety (that is, to minimize crime). Or, police may seek greater or lesser social control over alternative social groups. In either case, the KPT conditions for efficient enforcement are unlikely to provide the appropriate test for the absence of discrimination. The extant literature has also discussed several plausible explanations of why biased policing might exist.

[7] See Close and Mason (2007) for a more complete discussion of the criticisms of the KPT test.

Accordingly, two empirical possibilities arise when we combine the social control discussion, the economics of identity framework, and our evaluation of the literature: i) racially or ethnically biased policing may occur when the race of the officer differs from the race of the driver; and, ii) all officers, regardless of race or ethnicity, may exhibit biased policing against drivers of racial or ethnic minority groups. Although we do not attempt to distinguish among the alternative explanations of biased policing, we do derive and empirically examine a more general outcomes test than those presented heretofore in the existing literature. We turn now to discuss our theoretical framework and to present a rank-order test whose application depends on the specific empirical assumptions that we are willing make regarding police practice.

2. Theoretical model

Consider an evolutionary game with two agents, drivers and officers (or troopers) (see Table 1). There are four strategies available to drivers: whether to commit a traffic violation ($0 \leq \lambda \leq 1$) in combination with whether to engage in a criminal activity ($0 \leq \chi \leq 1$). Traffic violations include such activities as speeding, driving without a valid driver's license, driving a vehicle with sufficiently impaired equipment such that it violates vehicle safety standards, failure to obey traffic signs, or other acts that are not necessarily criminal but that do warrant police sanction. Traffic violations are the major reason any driver is stopped. For example, in our sample, speeding (70 percent of drivers) is the major traffic stop rationale. Drivers who do not engage in traffic violations are unlikely to be stopped by state troopers. We designate $\overline{\chi}$ as the fraction of all drivers "at risk" of committing a crime. A certain fraction of drivers ($1 - \overline{\chi}$) will not engage in criminal activity regardless of the policing strategy of law enforcement agencies; hence, $\chi \leq \overline{\chi}$ is the actual fraction of drivers engaged in criminal activity.

Table 1. Trooper—Driver traffic search game

					Driver: Traffic Violation (λ), Crime (χ)	Driver: Traffic Violation (λ), No Crime ($1 - \chi$)	Driver: No Violation ($1 - \lambda$), Crime (χ)	Driver: No Violation ($1 - \lambda$), No Crime ($1 - \chi$)
Trooper	Observed (ρ)	Stopped (σ)	Suspicious (ε)	Involuntary Search ($\bar{\gamma}$)	$v^p + f$, $v^d - j + y - f$	$v^{\bar{\gamma}} + f - t^{\bar{\gamma}}$, $y - f - c^{\bar{\gamma}}$	v^p, $v^d - j$	$v^{\bar{\gamma}} - t^{\bar{\gamma}}$, $u - c^{\bar{\gamma}}$
				Voluntary Search (γ)	$v^p + f$, $v^d - j + y - f$	$v^{\gamma} + f - t^{\gamma}$, $y - f - c^{\gamma}$	v^p, $v^d - j$	$v^{\gamma} - t^{\gamma}$, $u - c^{\gamma}$
				No Search ($1 - \bar{\gamma} - \gamma$)	$v^{\varepsilon} + f$, $v^d + y - f$	$v^{\varepsilon} + f - t^{\varepsilon}$, $y - f - c^{\varepsilon}$	v^{ε}, v^d	$v^{\varepsilon} - t^{\varepsilon}$, $u - c^{\varepsilon}$
			Not Suspicious ($1 - \varepsilon$)		f, $v^d + y - f$	$f - t^{\sigma}$, $y - f - c^{\sigma}$	v^{σ}, v^d	$v^{\sigma} - t^{\sigma}$, $u - c^{\sigma}$
		Not Stopped ($1 - \sigma$)			0, $v^d + y$	0, y	0, v^d	0, u
	Not Observed ($1 - \rho$)				0, $v^d + y$	0, y	0, v^d	0, u

Notes: $\lambda \equiv$ probability a driver commits a traffic violation ($0 \leq \lambda \leq 1$), $\chi \equiv$ probability a driver is engaged in a criminal activity ($0 \leq \chi \leq 1$), $\rho \equiv$ probability a driver is observed by police, $\sigma \equiv$ probability that an observed driver is stopped, $\varepsilon \equiv$ probability that troopers are suspicious of a stopped driver, γ, $\bar{\gamma}$ $\equiv$probability of voluntary or involuntary search of suspicious drivers, respectively, $v^d \equiv$ driver's valuation of criminal activity, $v^p \equiv$ police's valuation of detecting an individual engaged in criminal activity, $y \equiv$ driver's benefit from traffic violation, f $\equiv$ fine for a driving violation (= police benefit for stopping a driver guilty of traffic offense), $c^{\sigma} \leq c^{\varepsilon} \leq c^{\gamma} \leq c^{\bar{\gamma}}$ $\equiv$ costs for non-suspicious stops, stops with no search, voluntary searches, and involuntary searches, respectively, of drivers with no criminal violation, $j \equiv$ driver's cost of engaging in and being found guilty of a criminal activity, $u \equiv$ utility payoff for a driver who does not engage in crime and who obeys the traffic laws ($u > 0$), and $t^{\sigma} \leq t^{\varepsilon} \leq t^{\gamma} \leq t^{\bar{\gamma}} \equiv$ the trooper's cost of stopping a driver, the trooper's cost of stopping but not searching a suspicious driver, and the trooper's costs associated with voluntary and involuntary driver searches, respectively, for drivers who are uninvolved in criminal activity.

Each trooper has six strategies, which flow from the probability of whether or not a driver is observed (ρ), whether an observed driver is stopped (σ), whether troopers are suspicious of a stopped driver (ε), and whether there is no search, a voluntary search (γ), or an involuntary search of a suspicious driver ($\bar{\gamma}$). A voluntary search occurs when a police officer asks and the driver consents to having his vehicle searched. Drivers may refuse the police request to search. All voluntary searches are highly discretionary. There are several involuntary searches, that is searches that occur against the will of the driver. High discretion non-voluntary searches include inventory search, plain view search, probable cause search, and stop and frisk search. Limited discretion non-voluntary searches include search incident to arrest and searches that occur with search warrant.

Let v^d represent the driver's valuation of criminal activity, while v^p represents the police's valuation of detecting an individual engaged in criminal activity. Drivers receive a benefit y when they carry out a traffic violation. For example, y might indicate the value of time saved when a driver speeds. There is a fine (f) for a driving violation (same as police benefit for stopping a driver guilty of traffic offense) and costs ($c^{\sigma} \leq c^{\varepsilon} \leq c^{\gamma} \leq c^{\bar{\gamma}}$) for non-suspicious stops, stops with no search, voluntary searches, and involuntary searches, respectively, of drivers with no criminal violation. Drivers incur a cost (j) when they engage in and are found guilty of a criminal activity.[8] A driver who engages in no crime and who obeys the traffic laws has a utility payoff of $u > 0$. Further, for drivers who are uninvolved in criminal activity, t^{σ} is the trooper's cost of stopping a driver (including the opportunity cost of the trooper's time and the political cost of stopping a non-suspicious driver); t^{ε} is the trooper's cost of stopping but not searching a suspicious driver (such a driver might be questioned by the trooper and perhaps even receive but refuse a voluntary search request); t^{γ} and $t^{\bar{\gamma}}$ are the trooper's costs associated with voluntary and involuntary driver searches, respectively; and, $t^{\sigma} \leq t^{\varepsilon} \leq t^{\gamma} \leq t^{\bar{\gamma}}$.

Drivers and troopers have only limited information. Drivers know the costs and benefits associated with alternative strategies (v^d, j, y, f, c^{σ}, c^{ε}, c^{γ}, and $c^{\bar{\gamma}}$), but they do not know 1) the fraction of drivers pur-

[8] We assume that if a criminal driver is searched the driver's crime will be uncovered and the driver will be convicted in court. We further assume that police do not falsely charge drivers. These are standard assumptions in the literature.

suing a particular strategy or the fraction of officers pursuing a particular strategy (χ, λ, ρ, σ, ε, γ, $\bar{\gamma}$) or 2) the incentive structure of officers (v^{ρ}, v^{γ}, $v^{\bar{\gamma}}$, v^{ε}, f, v^{σ}, t^{σ}, t^{ε}, t^{γ}, and $t^{\bar{\gamma}}$). Similarly, troopers know their own incentive structure but they do not know the distribution of strategies among drivers or officers and they do know the incentive structure of drivers. Each driver selects a strategy and compares his payoff to drivers playing the same or different strategies. If a driver playing a different strategy has a superior payoff, the driver with the inferior outcome changes to the strategy of the driver with the superior payoff. Similarly, officers compare their strategies with the strategies played by other officers. Police strategies with the highest payoff are imitated while those with lower payoffs are eliminated. Equilibrium is established by competitive elimination of strategies with inferior payoffs.

2.1. Equilibrium

Let D_i, $i = 1, 2, 3, 4$, represent the four driver strategies and O_τ, $\tau = 1, 2, 3, 4, 5, 6$, represent the six officer strategies. The replicator dynamic for this system is

$$\dot{D}_i = D_i\left[E(D_i) - E(Driver)\right], i = 1,2,3,4 \text{ and}$$

$$\dot{O}_\tau = O_\tau\left[E(O_\tau) - E(Officer)\right], \tau = 1,2,3,4,5,6.$$

Often, the replicator dynamic for games of this sort suggests a corner solution as the stable outcome. However, working from observed outcomes back to our theoretical model we know that the equilibrium is an interior solution. Or, even if the dynamics suggest a corner solution in the long run for one-time perturbations of equilibrium it may be the case that the model is subjected to multiple and continuous perturbations and is unable to move unimpeded to long run equilibrium.

We may derive equilibrium via the payoff functions of the officers and drivers. (Without loss of generality, the derivation of the reaction functions makes no distinction between voluntary and involuntary searches).

Officers seek the optimal search rate such that

$$\frac{dE(Officer)}{d\gamma} = \rho\sigma\varepsilon\left[\chi v^{p} + (1-\chi)v^{\gamma} + \lambda f - (1-\chi)t^{\gamma}\right] + \rho\sigma\varepsilon\left[v^{\varepsilon} + \lambda f - (1-\chi)t^{\varepsilon}\right] = 0,$$

which yields the reaction function

$$\chi = \chi\left(\rho\sigma, \varepsilon, v^{p}, v^{\gamma}, \lambda, f, t^{\gamma}, v^{\varepsilon}, t^{\varepsilon}\right).$$

Accordingly, χ^* is a vertical line in (γ, χ) space. If $\chi < \chi^*$ no drivers will be searched, though at $\chi > \chi^*$ all drivers will be searched. If officers are idiosyncratic then the reaction function will be upward sloping.
Drivers seek the optimal crime rate such that

$$\begin{aligned}\frac{dE(Driver)}{d\chi} &= \lambda\left[v^{d} - \rho\sigma\varepsilon\gamma j + y - \rho\sigma f\right] \\ &- \lambda\left[y - \rho\sigma f - \rho\sigma\varepsilon\left\{\gamma c^{\gamma} + (1-\gamma)c^{\varepsilon}\right\} - \rho\sigma(1-\varepsilon)c^{\sigma}\right] \\ &- \lambda\left[v^{d} - \rho\sigma\varepsilon\gamma j\right] - (1-\lambda)\begin{bmatrix} u - \rho\sigma\varepsilon\left\{\gamma c^{\gamma} + (1-\gamma)c^{\varepsilon}\right\} \\ -\rho\sigma(1-\varepsilon)c^{\sigma} \end{bmatrix} = 0,\end{aligned}$$

which yields the reaction function

$$\gamma = \gamma\left(u, \rho\sigma, \varepsilon, v^{d}, j, y, \lambda, f, c^{\gamma}, c^{\sigma}, c^{\varepsilon}\right).$$

Accordingly, γ^* is a horizontal line in (γ, χ) space. If $\gamma < \gamma^*$ all (or, at least $\overline{\chi}$) drivers will commit an offense, though at $\gamma > \gamma^*$ no driver will commit an offense. If drivers are individually distinctive then the reaction function will be downward sloping.

Both public safety and the hit are maximized at (γ^*,χ^*). As we show below, when either officers or drivers are diverse the hit rate—maximizing equilibrium outcome is not the same as the safety—maximizing (or crime-minimizing) equilibrium outcome.

2.2. Rank-order test

The most general traffic search game occurs when drivers are racially diverse in criminal behavior and police are racially diverse in their search practices. Here we present a rank-order test, where the null hypothesis is no racial or ethnic discrimination.[9] The test includes search conditions (i) and no arbitrage conditions (ii). The search conditions are derived from the assumptions we make on officer and driver diversity. The no arbitrage conditions are needed to determine the absence of discrimination; hence, rank-order tests which ignore the no arbitrage conditions will necessarily have limited power but even when the no arbitrage conditions are met rank-order tests often have power < 1. If the equilibrium search conditions are true then our assumptions on driver and officer heterogeneity are likely also true; nevertheless, if the no arbitrage conditions are not fulfilled then we may conclude that discrimination exists.

Per our theoretical model, if motorists are idiosyncratic in the cost of committing crime (for example, carrying drugs) and officers are individually distinctive in the cost of searching motorists, then officer reaction functions will be smooth and upward sloping and driver reaction functions will be smooth and downward sloping (See also Antonovics and Knight, 2004).[10] This game permits a safety—maximizing equilibrium where variation in hit rates by race of driver and race of officer is consistent with the absence of discriminatory policing. For illustrative purposes, assume that white officers search more intensely than African American officers and that white drivers are less criminal than African American drivers. Per Figure 1, the equilibrium search conditions require the maximum search rate (shown at point $E_{a,W}$) for the combination of officers with the most intense search practices and drivers with the most criminal activity. The minimum search rate (equilibrium at point $E_{w,A}$) will occur for the combination of officers with the least intense search practices and drivers with the least criminal activity. The no arbitrage conditions require that we observe the maximum hit rate for the combination of officers with the least intense search practices and drivers with the

[9] See also Close and Mason (2003b, 2006) for a rank-order procedure to test for racial and ethnic discrimination in trooper enforcement actions.

[10] Possible reasons for upward-sloping trooper response function include: 1) trooper heterogeneity in the cost of search (Antonovics and Knight, 2004), 2) differential signals of guilt provided by drivers (Bjerk, 2004), or 3) unobservable characteristics of drivers (Antonovics and Knight, 2004).

most criminal activity. (See point $E_{a,A}$). The minimum hit rate will occur for the combination of officers with the most intense search practices and drivers with the least criminal activity, that is, point $E_{w,W}$.

The appropriate safety-maximizing rank-order test for efficient enforcement is as follows.

$$\text{max search rate } = \gamma(a,W) > \gamma(w,A) = \text{ min search rate, and} \tag{1.i}$$

$$\text{max hit rate } = \chi(a,A) > \chi(w,W) = \text{ min hit rate.} \tag{1.ii}$$

As we have discussed, the AF alternative version of this test restates the equilibrium search conditions and no arbitrage conditions as follows.

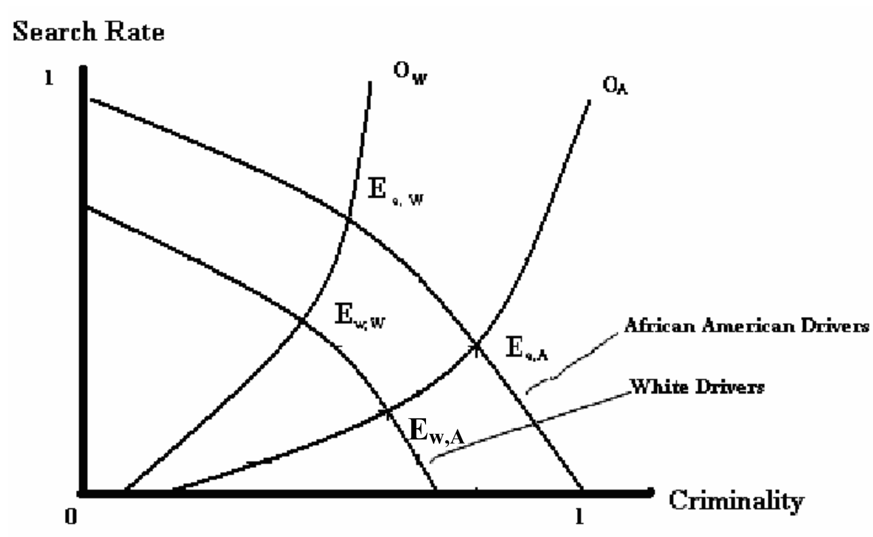
$$\gamma(w,W) > \gamma(w,A) \text{ and } \gamma(a,W) > \gamma(a,A), \tag{AF.i}$$

$$\chi(w,W) < \chi(w,A) \text{ and } \chi(a,W) < \chi(a,A). \tag{AF.ii}$$

The AF alternative test for efficient enforcement when both drivers and officers are racially heterogeneous has less power than the outcomes test presented here because AF do not utilize all of the information presented by the pattern of equilibrium outcomes. Specifically, the AF alternative test dispenses with any information regarding which group of drivers is the high crime group and which is the low crime group. So, the AF alternative test cannot distinguish between equilibrium outcomes with heterogeneous officers but homogeneous drivers and equilibrium outcomes with heterogeneous officers and heterogeneous drivers. Concluding, the AF alternative is an extremely limited alternative test since provides no information on efficient enforcement; it tells us only that there may be differences in search activity by officers of different racial or ethnic groups.

Figure 1 does not present the hit rate-maximizing equilibrium outcomes. The equilibrium outcomes presented in Figure 1 are consistent with correct expectations of driver criminality by all officers. In this example, African American officers have a higher signal threshold for criminal behavior than white officers. Therefore, white officers engage in relatively more searches of both white and African American drivers than African American officers. African American drivers in this illustrative example are more criminal than white drivers, therefore all officers regardless of race or ethnicity have higher search rates and higher hit rates for African American drivers than white drivers. But, the mere fact that white officers and African Americans have correct but different information (criminal expectations) and different policing strategies when facing the same population of drivers means that there is an opportunity for search arbitrage, especially if police share information.

Figure 1. Traffic search game with diverse drivers and diverse officers



The hit rate- maximizing equilibrium requires that white officers should have identical hit rates for African American and white drivers, even though they will have a higher search rate for African American drivers. Similarly, the hit rate-maximizing equilibrium for African American officers requires identical hit rates for African American and white drivers, even though they will have a higher search rate for African American drivers. If racially differential search by officers exists, the hit rate-maximizing equilibrium in the traffic search game must meet the following conditions.

$$\gamma(w,W) > \gamma(w,A) \text{ and } \gamma(a,W) > \gamma(a,A), \tag{2.i}$$

$$\chi(w,W) < \chi(a,W) \text{ and } \chi(w,A) < \chi(a,A). \qquad (2.ii)$$

The FHP is a state police agency, where all officers undergo identical training and where each officer is subject to the same command structure. So, it is unlikely to be the case that the traffic search game will be in hit-rate maximizing equilibrium with racially differential search activity by its officers. If so, KPT.i and KPT.ii provide the appropriate hit-rate maximizing hypothesis.

3. Empirical analysis

The data are the Florida Highway Patrol's Traffic Stop Data Reports and FHP's Characteristics of Troops dataset. The combined data sources yield a unique and rich dataset, which was originally analyzed in Close and Mason (2002).[11] The FHP's Traffic Stop Data contains all traffic stops made by sworn personnel form January 2000 to May 2002. Information from the Traffic Stop Data Report includes the county, date of the traffic stop, the trooper's identification number, and the assigned troop identifier. The stopped vehicle is identified by state of registration. Drivers are identified by race, ethnicity, sex, and driver's age. The driver's ethnicity includes whether or not the individual is Latino. Racial categories include black, white, Asian, and Native American (American Indian or Alaskan). Latino drivers may belong to any racial category. Additional information in the dataset includes the number of passengers in the vehicle, the reason for the traffic stop, search type, and rationale for consent search. The Characteristics of Troops dataset includes the officer's identification number, date of birth, race, and sex. Unlike Latino drivers, Latino officers are separate from all other racial groups. The combined dataset will allow us to determine whether and to what extent there are racial, ethnic, and gender differences in traffic stops and driver treatment after a stop has occurred.

[11] AF also use this data. Although AF is a derivative of the work of Close and Mason (2002) and related working papers, AF use only the data from January 2000 to November 2001. There is no explanation of why they do not use all of the study's data, though the sample they utilize includes over 900,000 observations.

3.1. Re-examination of Anwar and Fang: Re-weighted data

The racial and ethnic composition of officers varies by geographical region of deployment. The racial and ethnic composition of the population and drivers also varies by county. AF wish to alter the raw data so as to simulate a scenario whereby the observed racial and ethnic composition of drivers is invariate across the race and ethnicity of officers. The re-weighted data are constructed such that the racial and ethnic composition of officers does not vary by administrative district. Roughly 70 percent of Florida's state troopers are Non-Hispanic white, while 30 percent are either Latino or African American. So, if a district has an above average fraction of white officers then a random sample of white officers is extracted and added to all the minority observations. Conversely, if a district has a below average fraction of white officers then a random sample of minority officers is extracted and added to all the white observations. For example, if the district has 85 white officers and 15 African American and Latino officers, then a random sample of 35 white officers is extracted and combined with the 15 African American and Latino officers. If a district has 55 white officers and 45 African American and Latino officers, then a random sample of 24 African American and Latino officers are extracted and combined with the 55 white officers.

Table 2 presents search rates and hit rates by race and ethnicity of officer and by race and ethnicity of driver for this re-weighted data. Analysis is limited to three social groups: African Americans, Latinos, and whites.[12] On the whole, only about 1 percent of drivers stopped by the FHP undergo a search. But, 0.81 percent of stopped white drivers are searched versus 1.35 percent and 1.34 percent of stopped African American and Latino drivers. Most searches do not result in a hit. The Latino hit rate is 11.5 percent, while the hit rates for African Americans and whites are 20.9 percent and 25.1 percent, respectively. Chi-square tests reveal that the differences in search rates and hit rates by race of driver and by race of officer have p-values < 0.001 (Close and Mason, 2006, 2003a; Anwar and Fang, 2006).

The statistically significant differences in search and hit rates by race of officer and by race of driver are informative. Specifically, they tell us that we cannot assume that criminality does not differ by race

[12] Table 2 in the text is an abbreviated version of Table 1 of Anwar and Fang. Native Americans and Asian Americans make up a trivial share of driver searches and FHP officers.

and ethnicity of driver and that policing behavior does not differ by race and ethnicity of officer. Hence, we examine the outcomes test under the most favorable assumptions for the efficient enforcement hypothesis; namely, white officer search intensity > Latino officer search intensity > African American officer search intensity and white driver criminality < Latino driver criminality < African American driver criminality. These are the most favorable assumptions for the test because Panel A of Table 2 reveals that all officers search African Americans at a greater rate than other groups. Panel A of Table 2 also shows that white officers have higher search rates than Latino officers, for any given race or ethnicity of driver, while Latino officers have higher search rates than African American officers.

Table 2. Search rate and average search success rates against motorist of different races (re-weighted data)

Race of Driver	Race of Trooper			
Panel A: Search Rate (percent)				
	White	**African American**	**Latino**	**All Troopers**
White	0.96	0.27	0.76	0.81
African American	1.74	0.35	1.21	1.35
Latino	1.61	0.28	0.99	1.34
Panel B: Average Success or "Hit" Rate (percent)				
White	24.30	39.40	26.00	25.1
African American	19.90	26.00	20.80	20.9
Latino	8.50	21.00	14.30	11.5

Source: Extracted for Anwar and Fang (2006).

1.i and 1.ii (see page 99) is a very general rank-order test and provides the most direct comparison with AF. It allows heterogeneity among both drivers and officers. For the African American-white pair wise comparison we have

$$\text{max search rate } = \gamma(a,W) = 1.74 > \gamma(w,A) = 0.27 = \text{ min search rate},$$

and

$$\text{max hit rate} = 39.4 \neq \chi(a,A) = 26.0 > \chi(w,W) = 24.3 \neq \text{min hit rate} = 19.9.$$

The search rates agree with the requirements of equation (1.i). The inequality for the hit rates is also correct, but the hit rates do not have the appropriate outcome for either the maximum or minimum hit rate. The data reject the null hypothesis that racially differential search behaviors by white and African American officers reflect only efficient enforcement.

For the white/Latino pair wise comparison we have

$$\text{max search rate } = \gamma(l,W) = 1.61 > \gamma(w,L) = 0.76 = \text{ min search rate,}$$

and

$$\text{max hit rate} = 26.0 \neq \chi(l,L) = 14.3 < \chi(w,W) = 24.3 \neq \text{min hit rate} = 8.5.$$

The search rates agree with the requirements of equation (1.i). The inequality sign for the hit rates is incorrect. Also, the hit rates do not have the appropriate outcome for either the maximum or minimum hit rate. The data reject the null hypothesis that racially differential search behaviors by white and Latino officers reflect only efficient enforcement.

For the African American/Latino pair wise comparison we have

$$\text{max search rate } = \gamma(a,L) = 1.21 > \gamma(l,A) = 0.28 = \text{ min search rate,}$$

and

$$\text{max hit rate} = \chi(a,A) = 26 > \chi(l,L) = 14.3 \neq \text{min hit rate.}$$

The search rates agree with the requirements of equation (1.i). The hit rates agree with the requirements of (1.ii). Hence, for the re-weighted data and assuming a public safety-maximizing equilibrium, we cannot reject the null hypothesis that Latino and African American officers do not differentially search Latino and African American drivers.

Equations (2.i) and (2.ii) provide the criteria for the hypothesis test of hit-rate maximizing efficient enforcement with differential policing by Latino and African American officers. The relevant search results are $\gamma(l, L) = 0.99 > \gamma(l, A) = 0.28$ and $\gamma(a, L) = 1.21 > \gamma(a, A) = 0.35$.

These results agree with the requirements of the efficient search conditions of (2.i). The relevant hit rates are $\chi(l, L) = 14.3 \neq \chi(a, L) = 20.8 < \chi(l, A) = 21.0 \neq \chi(a, A) = 26.0$, which do not agree with the no arbitrage conditions of (2.ii). Hence, for the hit-rate maximizing equilibrium, the data reject the null hypothesis that ethnically differential treatment of Latino and African Americans drivers by Latino and African American officers represents efficient enforcement rather than discriminatory treatment.

3.2. Analysis of raw data

In an attempt to establish a comparative benchmark, the AF re-weighting procedure may introduce bias in the testing process. Specifically, the rationale for the AF re-weighting procedure is that the characteristics of drivers vary across administrative districts. If this is not the case the AF simulation may create a sample that yields biased results.

Tables 3a and 3b present the raw (unaltered) search rates and hit rates by race, ethnicity, and administrative unit. We may apply both the outcomes test presented in this paper (1.i and 1.ii) and the AF test to search rates and hit rates derived from the raw data of 10 administrative units. We limit our observations to males. Additional analysis shows that repeating these outcomes tests using African American and white women will not alter any of our conclusions. Also, Latina stops by African American and Latino officers are too few to use in the analysis.

For each district we carry out pairwise comparisons for white males/African American males, white males/Latinos, and African American males/Latinos. Hence, there are 30 comparisons. Using the AF test, 22 of 30 pairwise comparisons reject the null hypothesis of no discrimination. The 8 pairwise comparisons that do not reject the null hypothesis of efficient enforcement include 3 white male/African American male comparisons (Troops C, G, and H), 3 white male/Latino comparisons (Troops D, E, and F), and 2 African American male/Latino comparisons (Troops C and G). Using 1.i and 1.ii, only 1 of 30 pairwise comparisons fails to reject the null hypothesis of no discrimination. In particular, the white male/African American male pairwise comparison for westcentral Florida (Troop C) cannot reject the null hypothesis of efficient enforcement.

Table 3a. Search rates, males, by race of officer, district of stop, and race of driver

			Officer	
Troop K (Florida Turnpike)				
		White	**African American**	**Latino**
Driver	**White**	0.0049	0.0060	0.0051
	African American	0.0096	0.0075	0.0084
	Latino	0.0057	0.0039	0.0069
Troop A (West Florida)				
		White	**African American**	**Latino**
Driver	**White**	0.0061	0.0012	0.0058
	African American	0.0104	0.0011	0.0049
	Latino	0.0489	0.0000	0.0000
Troop B (North Central)				
		White	**African American**	**Latino**
Driver	**White**	0.0066	0.0004	0.0042
	African American	0.0119	0.0039	0.0193
	Latino	0.0179	0.0000	0.0194
		White	**African American**	**Latino**
Driver	**White**	0.0212	0.0026	0.0121
	African American	0.0425	0.0051	0.0189
	Latino	0.0626	0.0110	0.0166
Troop D (East Central)				
		White	**African American**	**Latino**
Driver	**White**	0.0066	0.0005	0.0029
	African American	0.0164	0.0012	0.0049
	Latino	0.0090	0.0009	0.0030

Table 3a. Continued…

Troop E (Dade and Monroe)

		Officer		
		White	**African American**	**Latino**
Driver	**White**	0.0128	0.0008	0.0054
	African American	0.0239	0.0030	0.0136
	Latino	0.0166	0.0017	0.0066

Troop F (South Western)

		White	**African American**	**Latino**
Driver	**White**	0.0139	0.0047	0.0050
	African American	0.0354	0.0043	0.0179
	Latino	0.0252	0.0062	0.0152

Troop G (North Eastern)

		White	African American	Latino
Driver	**White**	0.0033	0.0046	0.0050
	African American	0.0099	0.0107	0.0043
	Latino	0.0116	0.0236	0.0025

Troop H (Capital Region)

		White	**African American**	**Latino**
Driver	**White**	0.0057	0.0003	0.0000
	African American	0.0099	0.0006	0.0089
	Latino	0.0241	0.0009	0.0000

Troop L (South Eastern)

		White	**African American**	**Latino**
Driver	**White**	0.0048	0.0015	0.0025
	African American	0.0084	0.0008	0.0053
	Latino	0.0080	0.0012	0.0030

Table 3b. Hit rates, males, by race of officer, district of stop, and race of driver

Troop K (Florida Turnpike)			
	Officer		
	White	African American	Latino
White	0.2879	0.4500	0.5217
African American	0.2222	0.2083	0.1600
Latino	0.1651	0.1429	0.3636
Troop A (West Florida)			
	White	African American	Latino
White	0.1881	0.6000	0.0000
African American	0.2014	0.0000	1.0000
Latino	0.0878		
Troop B (North Central)			
	White	African American	Latino
White	0.3193	0.0000	0.2222
African American	0.2185	0.6667	0.0000
Latino	0.0357		0.5000
Troop C (West Central)			
	White	African American	Latino
White	0.2095	0.2571	0.1795
African American	0.2217	0.5556	0.1250
Latino	0.0704	0.2857	0.2632
Troop D (East Central)			
	White	African American	Latino
White	0.2828	0.5714	0.5652
African American	0.2500	0.2000	0.2857
Latino	0.1343	0.5000	0.1429

Table 3b. Continued….

	Troop E (Dade and Monroe)		
	Officer		
	White	African American	Latino
White	0.1319	0.2857	0.2353
African American	0.0649	0.0000	0.1892
Latino	0.0645	0.1379	0.2034
	Troop F (South Western)		
	White	African American	Latino
White	0.2442	0.4348	0.3590
African American	0.2151	0.0000	0.1364
Latino	0.1560	0.0000	0.1892
	Troop G (North Eastern)		
	White	African American	Latino
White	0.3402	0.1972	0.0000
African American	0.3133	0.2857	0.0000
Latino	0.1463	0.1500	0.0000
	Troop H (Capital Region)		
	White	African American	Latino
White	0.1903	0.5000	
African American	0.1458	0.0000	0.0000
Latino	0.0577	0.0000	0.3333
	Troop L (South Eastern)		
	White	African American	Latino
White	0.2607	0.1892	0.3333
African American	0.1897	0.1429	0.3333
Latino	0.1717	0.4444	

Concluding, our non-parametric results show that there is evidence of police bias against African American and Latino drivers by all officers. Second, white officers search drivers most intensively, while African American officers search drivers the least intensely. Third, using raw data or re-weighted data does not change our conclusions. Fourth, previous tests proposed in the literature (KPT and AF) are less definitive than the outcomes test proposed here. Parametric results also show that white officers are more likely to search drivers than African American and Latino officers, even after controlling for the traffic stop rationale, an officer's cause of suspicion, characteristics of the driver, administrative unit and year of the stop, characteristics of the stop location, and additional characteristics of the officer (Close and Mason, 2007).

4. Conclusions

Biased policing against racial and ethnic minorities is an important public policy issue. Theoretical analysis and empirical research on this issue has been plagued by the usual set of problems which confront research on discrimination against social groups. At a theoretical level, models of discrimination must explain persistence, that is, they must explain why discrimination will exist within the context of arbitraging behavior and equilibrium outcomes. At an empirical level, the omitted variables problem is ever present.

Knowles, Persico, and Todd (2001) and Anwar and Fang (2006) proposed outcomes tests that are simple to employ and which attempt to elude the problems associated with establishing a comparative benchmark. However, the extant literature has shown that there are several problems with the KPT test, while one of its major refinements (the Anwar and Fang test) has limited power for determining discrimination. Anwar and Fang's proposed alternative test has at best only marginal because it fails to take account of information on racial and ethnic differs in driver criminality (if there are any).

This paper presents a more general outcomes test and which has greater power than the KPT and AF tests. Our empirical results contradict the central finding of Anwar and Fang; namely, an appropriately designed outcomes tests strongly rejects the null hypothesis that FHP troopers of different races do not engage in racial prejudice. Specifically, our non-parametric results show that there is evidence of racial and ethnic discrimination in police searches of African American and Latino drivers by all officers (white, Latino, and African American). Second, white officers search drivers most intensively, while African American officers search drivers the least intensely. Third, using raw data or re-weighted data does not change our conclusions.

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