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Race-Sensitive Choices by Police Officers in Traffic Stop Encounters

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Abstract

This study introduces a statistical estimator that can be used to examine disproportionate traffic stop behavior of police officers. This estimator can be employed in concert with internal benchmark data and a tree diagram algorithm to identify and classify disproportionate behavior. These methodologies are multilevel and can be used (a) at the macrolevel to examine disproportionality of a police department as an organization and (b) at the microlevel to draw inferences about reasons for individual officers' disproportionate behavior. These statistical routines were tested using data from a medium sized midwestern community. Results suggest that the models are effective in detecting disproportionality in both a police organization and an individual officers' traffic stop activity. Moreover, the methods may serve as an initial step in pointing toward the sources of the officers' behavior.

Keywords

racial profiling, minority, race, racial, stereotyping, discrimination, police, officer, disproportionate, disproportionality, cognitive bias, cognitive activity, traffic analysis, baseline

Introduction

Judgments regarding the discretionary behavior of the police when dealing with minorities stir deep-seated emotions concerning the fairness and equity of the criminal justice system. Currently, one of the most visible expressions of this activity is traffic enforcement involving non-White drivers. This type of police conduct inspires heated and passionate debate. At the core of this discussion is a simple and fundamental question: Are the police using race to disproportionately single out non-Whites for traffic stops, searches, and citations? Although the intent of the officers is not clear, the bulk of the recent research evidence suggests there is racial disparity in police traffic stop behavior (for reviews, see Batton & Kadleck, 2004; Engel, Calnon, & Bernard, 2002).

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Though the extant research is timely, valuable, and informative, it is not without certain limitations. These shortcomings center on methodological and theoretical issues. First, most previous research has struggled to deal with the baseline problem—a method for determining the percentage of non-White drivers in the target population. The baseline is a comparison standard that can be thought of as the percentage of minority drivers that should be stopped in a given jurisdiction when no disproportionate police activity is occurring.

Second, most previous research has wrestled with the challenge of defining and isolating the theoretical processes generating traffic stop disparities. Essential terms including *profiling, stereotyping, discrimination*, and *racism* have been used interchangeably or lumped together under fuzzy designations like driving while Black. The ambiguity surrounding fundamental concepts has impeded theoretical progress and made it difficult to segregate and classify the effects of potentially disparate forms of racial disparity.[1]

Finally, most previous research has attempted to uncover racial disparity at the level of an organization, to the exclusion of officer-to-officer comparisons. However, the statistical models used in organizational-level analysis rarely explain all the variance observed in the outcome variables. This is often because key pieces of information, including important premises and concepts, are not quantifiable or available for use in the model.

This study complements the existing literature by serving as an initial step in redressing some of the limitations of previous research. The current investigation uses an observational baseline to examine the traffic stop behavior of a police department we call Corner City P. D.[2] The research methodology is anchored by a statistical algorithm that identifies disproportionate behavior at the level of an officer. This estimator can be used to look for patterns in a particular officers' behavior. Accordingly, the method serves as an early warning system for analysts in the initial identification of a variety of potentially malevolent police behaviors. The methodology also uses officer-to-officer comparisons. These types of comparisons examine similarly situated officers and so may be used to construct an internal benchmark (Alpert, Dunham, & Smith, 2007). This standard is helpful in the interpretation of findings for racially biased policing that may be generated by omitted variables. Finally, this benchmark is used in tandem with abstract theoretical models as an initial step in identifying the social psychological and social structural sources of disproportionate behavior and is useful in providing a qualitative context that can be used to juxtapose and evaluate the reasonableness of these competing explanations.

Background and Review

Historical Antecedents

Racial disparity within the criminal justice system is an enduring feature of the American experience. For most of this country's history, African Americans have been overrepresented at nearly all stages of the criminal justice process (Drummond, 1999; Kennedy, 1997; for a contrasting opinion, see DiLulio, 1996; Wilbank, 1987). However, studies conducted over the past 30 years suggest change. These studies have consistently indicated that the use of race in police decision-making behavior has been steadily decreasing (Engel et al., 2002; Sherman, 1980). This is likely due in part to community outrage and legislative action and partly because of efforts by police supervisors. Today most research suggests that police discretionary decision making is predicated more on legal and situational factors than on race per se (Engel et al., 2002; Mastrofski, Worden, & Snipes, 1995; Riksheim & Chermak, 1993). Nevertheless, race remains one of the most reliable predictors of attitudes toward the police in America today (Weitzer & Tuch, 2005). African Americans are consistently more likely to hold negative opinions of the police than are other groups (Hurst, Frank, & Browning, 2000).

Why then, at a time when overt racism by the police seems to be decreasing, do African Americans cling to negative perceptions of the police? In part, the answer may lie in a perception of double disproportionality—an opinion by African Americans that the police tend to energetically enforce the law against them but fail to adequately enforce the law for them. Certain police and law enforcement practices may serve to heighten this suspicion. The notable forms of drug courier profiling that began in the last quarter of the 20th century provide an example.

Profiling in various forms has existed for decades in the United States and at times has been an acceptable police practice (e.g., when a gang unit uses a profile to identify members).[3] However, the practice became particularly controversial in the 1980s when some of the first federally subsidized drug courier profiling methods were developed and used to train local law enforcement officials. An example of this approach includes commonly used tactics developed in a Drug Enforcement Administration–sponsored profiling strategy called *Operation Pipeline*. This program was originally designed to stem the flow of drugs that were being transported from Florida to the metropolitan areas of the Northeast along interstate highways. Officers participating in this training were taught guidelines for identifying the typical characteristics of drug couriers. One of these characteristics included race. Consequences of this activity were increased levels of fear and resentment among African American's toward police, which lead ultimately to lawsuits and litigation.

Two Conceptual Challenges in Recent Research

The acknowledgment of racial profiling in traffic stops is generally traced back to two court cases in the 1990s. Defendants in a New Jersey criminal case, the *State of New Jersey vs. Soto* (1996), and plaintiffs in a Maryland civil case, *Wilkins vs. Maryland State Police* (1993), argued that they were stopped because of their race rather than their driving. This litigation sparked scholarly interest in this subject and a spate of court cases across the country. As a result of this legal action, many more police departments began collecting data on police–citizen contacts.[4]

Unfortunately, much of this data remains untouched. A key reason for this neglect is difficulty in identifying and developing the essential characteristics of the data. The question of how to develop an effective baseline is one of these problems. A baseline is a standard for determining the percentage of minority drivers in a given police jurisdiction. Investigators compare this benchmark to police traffic stop data to determine whether the driver's race was a factor in the officer's decision to make a traffic stop. Some methods of benchmarking include using census or DOT information to establish baselines. These techniques are often ineffective for various reasons, including differences between races in the amount of time spent driving (driving quantity), racial differences in offending rates and thus police attention (driving quality), and the racial composition of neighboring communities whose citizens may travel through the population of interest (driver mobility). More recent innovations, however, use mixed methodological approaches that combine direct observation with accident and other data. These methods have generally established more valid baselines than earlier attempts (e.g., Alpert et al., 2007; Alpert, Smith, & Dunham, 2004; Lamberth, 2006).

The question of how to define racial disparity in traffic stops is a second conceptual difficulty that has restrained empirical analysis and impeded theoretical progress. The concept of *racial disparity* or profiling takes on different meanings depending on who is using it with at least 20 different definitions cataloged in the literature (Batton & Kadleck, 2004). Although parts of these definitions are distinct, most share central themes. For instance, nearly all imply that profiling occurs; when at a minimum, officers use race as a factor in deciding whether to stop or sanction a motorist. The etymology of these definitions can be thought of as existing on an imaginary continuum anchored by purely social psychological explanations on one end and exclusively social structural accounts on the other. Some of the ambiguity surrounding profiling definitions may stem from a failure to uniformly identify, isolate, and define the root elements of disproportionality. In the next section, we examine four fundamental sources of racial disparity in police traffic behavior.

Sources of Disparity in Officers' Conduct

Several researchers suggest that at least one of the four following processes is likely to be present in any context where race-sensitive choices are made by the police (Batton & Kadleck, 2004; Novak, 2004; Novak & Chamlin, in press; Smith, Makarios, & Alpert, 2006; Tomaskovic-Devey, Mason, & Zingraff, 2004). The first two of these processes are a product of human agency and stem from social psychological sources. The final two processes are informed by patterns of behavior generated by social structural norms and expectations.

Discrimination and prejudice. Discrimination is negative behavior directed toward persons based on their membership in a group (Nelson, 2006). Discrimination is an observable conduct and, in many instances, is a byproduct of racial *prejudice,* defined as a preconceived attitude toward a racial group and its individual members (Myers, 2008). Prejudice is an internal evaluative response to a social context. A prejudiced person carries a set of fixed and rigid beliefs and feelings about other people, groups, or practices. This cognition and affect are difficult to alter. Although prejudice can be positive or negative, the negative form often leads to discrimination. The sources of prejudice include socialization, innate personality characteristics, ethnocentrism, intergroup competition for scarce resources, and frustration-aggression (Smith & Alpert, 2007). Negatively prejudiced people carry a resolute dislike for members of another group. This antipathy increases the likelihood that they will discriminate or exhibit unjustified negative behavior toward a person from the disliked group. In a police setting, for instance, prejudiced White officers might act on their antipathy for non-Whites in contexts where the officer has a lot of discretion. For example, the officer may closely scrutinize vehicles driven by people of color and demonstrate an unwillingness to overlook infractions involving minority drivers. The end result is disproportionate stopping and sanctioning of minority drivers.

Unconscious cognitive activity. However, not all prejudice is mindful. Prejudice can be explicit and conscious or implicit and automatic. Accordingly, unfavorable evaluations of others can surface outside a person's deliberate awareness (Bargh & Chartrand, 1999). Often this implicit biased appears subtly and is the product of automatic cognitive processing (Payne, 2001). This nonvolitional cognition occurs very rapidly and without any conscious executive decisions being made about the process (Huesmann, 1998).

Automatic prejudice develops from the twin processes of *categorization* and *stereotyping*. The later is defined as a thinking shortcut consisting of overgeneralized beliefs used to organize and simplify the social world (Macrae & Bodenhausen, 2001). The former is an involuntary cognitive process that prompts people to classify others into discrete groups such as those based on race. Established classifications activate associated beliefs (stereotypes) and attitudes (prejudices) in regards to the categories. These beliefs and attitudes are learned through routine interaction and media representations, such as television and movies. In the industrialized world, many stereotypes, including those linked with race, are so prominent that nearly all members of a given society are aware of them (Devine, 1989). Recently, Smith et al. (2006) argued that the police may develop implicit cognitive schemas that generate suspicion in officers for subgroups that are associated with crime and violence. Implicit stereotyping and prejudice then are by-products of normal cognitive activity. To illustrate this in the context of police work, imagine a setting where a White officer is patrolling a wealthy and predominately White residential area. Categorization occurs when the officer observes an African American in the vicinity. This process typically activates an awareness of race. This link becomes stereotyping if it is accompanied by cognition that guides interpretation of the context. For instance, the officer may experience a gut feeling or hunch informing her that the African American is suspicious because he seems out of place. If so, the officer's experience is typical of the transformation from a simple categorization into stereotyping. The officer's reaction is likely based in part on illusionary correlational mechanisms formed from traces of previous experience that mediate her existing beliefs about the personal attributes of a group of people.[5] Carrying the illustration further, stereotyping turns into subtle forms of bias when the officer decides to act on her gut feeling by stopping this suspicious subject for investigation. Because this process is automatic, the officer is likely not aware that she is acting in a biased fashion. In fact, the officer may deny holding any negative attitudes, feelings, or beliefs about African Americans. Because of this, the officer is far less likely than an overtly prejudiced officer to officially sanction the suspicious subject with a reprimand, ticket, or arrest.

Racial profiling in traffic stops. Racial profiling refers to the explicit use of race as one in a set of characteristics employed in determining the suspiciousness of a person. In a traffic context, a profile is an unambiguous list of identifiers intended for use by officers to recognize occupants of vehicles who are likely to be engaged in criminal activity. The use of a profile is strategic activity (Smith & Alpert, 2007) that is often used to identity drivers or vehicles carrying drugs, weapons, or contraband.[6] Racial profiling in traffic stops can be grouped into two fundamental types. Organizational profiling is authorized and taught by law enforcement managers. Examples include the institutionalized forms of traffic profiling like Operation Pipeline. For the street officer, this type of profiling is generated by social structural forces. Officers' actions are guided by organizational rules, training, and expectations. Consequently, organizational norms are primarily responsible for generating disparity. In contexts where this occurs, profiling tends to be widespread among the rank and file.

Individual profiling is neither endorsed by the organization nor taught by police management personnel. Instead, officers learn the practice informally from each other or pick up the techniques on their own. Human agency and individual choice are largely responsible for this conduct, and so this type of profiling is generally not as widely practiced within a department as organizational profiling.

Often the goal of profiling is interdiction. For both organizational and individual types of profiling, the process of interdiction consists of two elements: a stop and a search. Studies of police special enforcement units that focus on interdicting drugs and weapons strongly suggest that officers assigned to these units disproportionately stop and search minority drivers (Smith & Alpert, 2007). Accordingly, disproportionality in traffic stops and searches, especially in isolation of other types of disproportionality, often is an expression of both organizational and individual types of racially motivated traffic profiling.

Directed patrol. Directed patrol is a police deployment technique that increases the odds the police will come in contact with minority members. This can result from geographic, temporal, or organizational factors. Geographically, this is a deployment strategy that leads to a disproportional number of officers patrolling in non-White areas of a community. This frequently occurs when police departments attempt to aggressively patrol areas of town with higher crime rates or calls for service. If these areas correlate with high concentrations of minority residents, then the odds increase that police officers will come into contact with minority residents through traffic stops, investigations, and searches. Temporal factors include police staffing schemes that increase contact between police and minority members. For example, heavily staffing nighttime or weekend patrol shifts to match call volume may increase the likelihood of police–minority contact, especially if these scheduling techniques correspond with minority driving patterns. Organizational factors include implementing special patrol strategies, such as aggressive gang investigation units, that increase police–minority interaction particularly when the targets are disproportionately represented by minority members. All these sources of disparity are generated by social structural forces. Factors like the demographic characteristics of a community, beat assignments, and organizational staffing policies account for disproportionality more than do officers' choices. Consequently, when looking for this type of disproportionality in an organization, researchers should find disparity clustered among officers working in particular areas of town, shifts, or assignments, rather than uniformly dispersed among all patrol officers.

In summary, even though research suggests that overt racism by the police is declining, minority members still distrust the police. These feelings may be the result of lingering forms of inequitable treatment by law enforcement. As described above, these forms of behavior have social psychological and social structural roots. In what follows, we analyze traffic stop data from the Corner City Police Department and use this information to identify four abstract models of disproportionate police conduct. These techniques serve as an early warning device in identifying officers whose traffic stop activity may be inequitable. If unfair treatment of minority drivers is found, the next step is to try and understand the officer's motivation for the disproportionality. Although it is impossible to infer an officer's psychological motivation solely from traffic stop behavior, our models may function as a rudimentary guidepost or tool that can be used to point the way for researchers to look when analyzing an officer's disproportionate behavior. Although the social psychological and structural processes discussed in this literature review are likely to be present in contexts where the police make race-sensitive choices, there are potentially a large number of alternative explanations that can account for police traffic stop disparity. Our models serve as a standard to compare the reasonableness of these competing explanations for disproportionality. We conclude the article by presenting a preliminary description linking these sources with our abstract models informed by the knowledge of competing explanations.

Method

Foundational Analysis

The initial process used to identify and evaluate disproportionality is described in this section. This process begins with a series of logistic regression analyses of the organization as a whole. These analyses are useful in detecting disproportionality at the macrolevel of an organization.

Data sources. This study examines data collected by the Corner City Police Department between June 1, 2007, and December 31, 2007. Corner City street officers record information relevant to self-initiated traffic activity as part of their regular duties. The Corner City Police Department has been collecting traffic stop data for approximately 10 years. Officers are very familiar with the data-collection routine. When stopping a vehicle, officers contact the dispatch center that logs the stop. The officers use their in-car computers to enter pertinent information at the completion of the stop. The data are then transmitted to the station where they are centrally stored.

Table 1. Descriptive Statistics and Variables Used in Multivariate Analysis

Variables	Values	Frequencies
Dependent		
Race	0 = *White or Asian*	4,721 (87.15%)
	1 = *Black, Hispanic, Native, or Other*	696 (12.85%)
Citation	0 = *no*	3,011 (55.58%)
	1 = *yes*	2,406 (44.42%)
Arrest	0 = *no*	5,162 (95.29%)
	1 = *yes*	255 (4.7%)
Search request	0 = *no*	5,330 (98.39%)
	1 = *yes*	87 (1.6%)
Independent		
Driver demographics		
Age of driver	Continuous	$\mu = 32.75, \sigma = 14.49$
Driver's gender	0 = *female*	2,032 (37.52%)
	1 = *male*	3,385 (62.48%)
Driver's residence	0 = *Corner City and James County*	3,964 (73.17%)
	1 = *other county and out of state*	1,453 (26.82%)
Vehicle registration	0 = *out of state*	407 (07.13%)
	1 = *in state*	5,010 (92.48%)
Seizure	0 = *no*	5,367 (99.07%)
	1 = *yes*	50 (0.92%)
Reason for stop		
Equipment violation	0 = *no*	3,425 (63.21%)
	1 = *yes*	1,992 (36.78%)
Moving violation	0 = *no*	2,048 (37.81%)
	1= *yes*	3,369 (62.18%)
Officer demographics		
Race	0 = *White*	5,325 (98.3%)
	1 = *Black*	94 (1.7%)
Gender	0 = *female*	310 (5.71%)
	1 = *male*	5,107 (94.28%)
Time working	0 = *night*	2,166 (39.99%)
	1 = *day*	3,251 (60.01%)
Years of service	Continuous	$\mu = 12.26, \sigma = 8.32$

During the 6-month study period, the Corner City Police Department conducted 5,417 traffic related police–citizen contacts. For each stop, officers entered data regarding the driver of the vehicle, the reason for the stop, and demographic information. Officers were unaware that their discretionary traffic stop behavior would be examined by outside researchers. It seems unlikely then that officers reduced their level of discretionary behavior during the analysis period over concerns of increased scrutiny. Table 1 lists descriptive statistics for the information collected by street officers during the study period as well as the variables used in logistic regression analyses that follow.[7]

Between June and December 2007, 12.85% of all drivers stopped by Corner City street officers were minority drivers. For theoretical reasons, we refer to all races other than Whites and Asians as minorities.[8] Roughly, 62.5% of all stopped drivers were men. Most drivers (73.15%) resided in Corner City or the neighboring unincorporated areas and were driving vehicles with in-state registrations (92.48%). Roughly, 60% of the drivers were stopped for moving violations, whereas about 37% were stopped for equipment violations. Just above half the drivers (55.58%) were issued warnings rather than citations (44.42%). Only 4.7% were arrested. The majority of the stops were made during daylight hours (60%) by White (98.3%) male (94.28%) officers. All the stops included in the analysis were officer initiated. No stops resulting from calls for service or from vehicles suspected of being involved in a reported crime were included in the analysis. All search requests were consent searches. These searches are only conducted in circumstances that do not meet the standards of probable cause.

Observational baseline information. During the study period, 14 trained observers monitored traffic in Corner City. These individuals were stationed at various locations within each of Corner City's four police beats. Several intersections were designated for observations within each beat. These intersections were chosen at random prior to the beginning of the study, after being screened for traffic volume and visibility (the selected intersections were chosen from a pool of relatively busy intersections). The choice of intersections proved to be less complex in Corner City than it might have been in other more heterogeneous communities because Corner City is comparatively uniform in terms of the racial composition of neighborhoods. In plain terms, there is no predominately African American or other minority sections of town. In fact, an examination of data from the 2000 U.S. census for the percentage of African American by block group reveals the following. Corner City is made up of roughly 30 block groups. Two of these block groups are populated with the highest concentrations of African Americans. These areas are located on different police beats. However, even in these highest concentration areas, the percentage of African Americans residing in either of these block group sections never exceeds 9.3%. In all other areas of the community, the percentage of African Americans populating any block group is less than 6.6%. A simultaneous examination of all block groups strongly suggests that on the whole, African American homes are more or less evenly distributed throughout the community.

For each selected intersection, every observer made between 200 and 400 traffic observations. Depending on traffic volume, this took approximately 45 minutes. Generally, observers examined traffic in at least one intersection on all four beats in a given session. Consequently, each observation session lasted roughly 3 or 4 hours. The observers surveyed vehicles to discern the race and gender of the drivers and conducted their inspections periodically all hours of the day—mornings, afternoons, evenings, and late nights. The observers used a systematic sampling strategy that was dependent on traffic volume. For example, when traffic volume was light, the observers would attempt to assess race and gender for each vehicle passing through the intersection. When traffic

Table 2. Corner City Traffic Observations and 2000 Census Information

Observations	Total	Percentage	Census percentage
White	19,391	88.14	87.3
Black	843	3.83	3.70
Asian	854	3.88	3.60
Other	912	4.15	5.40
Grand total	22,000		
White and Asian	20,245	92.02	91.0

Note: $\chi^2 = 148.68$. $r = .999$.

volume was heavier, an assessment was made for a set number of cars (e.g., every third car) passing through the intersection. Generally, traffic volume was much lighter late at night than during daytime or evening hours. Therefore, the length of observation periods tended to be longer at night than during daylight hours. Because the observers worked independently of one another, the correlation coefficient r was used to assess interobserver reliability. The assessments from each observer were compared across all beats. Accordingly, each observer's observations were compared to all others. For example, the correspondence of assessments of race across all observation points from Observer A were compared to those same observation points for Observer B. Observer B's data were next compared to observer C's and so on. This was done for all possible contrasts, for a total of 91 comparisons. The average correlation of assessments between observers was extremely high ($r = .989$). This strongly suggests that the roadside observers were independently seeing very similar percentages of minority and nonminority drivers pass through each observation site.

The observers made an assessment of race for 22,000 drivers between June and December 2007. Table 2 depicts the findings as well as the parallel 2000 census figures.

The correspondence between the percentages witnessed by the roadside observers and the 2000 census population percentages is striking; 92.02% of their assessments were of White or Asian drivers, whereas 7.98% were minority group members. This closely resembles the 2000 census figures, which report that 91% of Corner City residents were White or Asian, and 9% were members of other racial groups. In addition, observers found that on each of Corner City's four police beats, the percentage of Whites and Asians was at least 91%, and there was no significant difference in percentages between daytime and nighttime hours.[9] Based on these findings and the high interobserver reliability, it seems reasonable to conclude that a valid and conservative baseline for Corner City driver demographics is 90% White and Asian, and 10 % minority. We will soon describe how the baseline is used in a disparity index and an odds ratio to examine individual officers' behavior.

Logistic regression analysis. As noted, 12.85% of all drivers stopped by Corner City officers during the study period were minority drivers. This figure is about 3% larger than the 10% minority baseline. However, does this discrepancy indicate a substantive

Table 3. Logistical Regression Analysis for Correlates Predicting Driver's Race

	Race		
Variable	*B*	*SE*	Exp(*B*)
Driver's age	−0.0053	.0031	0.9947
Male driver	0.2791**	.0887	1.322
Out-of-state driver's license	−0.4920***	.1232	0.6114
In-state registration	−0.9524***	.1721	0.3858
Equipment	0.3023*	.1484	1.353
Moving	−0.0934	.1475	0.9108
Seizure	1.061***	.3076	2.891
Black officer	0.4620	.2955	1.587
Male officer	0.2929	.1869	1.340
Working days	−0.3241***	.0922	0.7232
Years of service	−0.0259***	.0058	0.9745
Constant	−0.8374***	.3093	
Model χ^2	161.668***		
Nagelkerke R^2	.055		

Note: *N* = 5,417. 1 = *African American, Hispanic, Native American, or a race other than White or Asian*; 0 = *White or Asian*.
*$p < .05$. **$p < .01$. ***$p < .001$.

difference? Does it signify that members of the Corner City Police are disproportionately singling out minority drivers for traffic enforcement? Multivariate analysis is the first step of the investigation in answering these questions. The findings from binary logistic regression are displayed in Tables 3 and 4. Table 3 depicts the correlates for predicting the driver's race given that a stop has occurred, whereas Table 4 shows the correlates for predicting certain outcomes of a stop, including citations, arrests, and search requests.[10] Both tables include unstandardized beta coefficients, their standard errors, and the log odds of the coefficients. The log odds (Exp[*B*]) shows the odds of a change in the dependent variable for a unit increase in one of the independent variables while holding all others constant.

Table 3 indicates whether the independent variables in the model are associated with race, given that a stop has occurred. A total of 7 of the 11 variables are significant net of the other variables. Three of these are associated with an increase in the odds of the driver being a minority member: (a) being a male (32%, increase in odds, $\beta = .2791$, $p < .01$), (b) being stopped for an equipment violation (35%, increase in odds, $\beta = .3024$, $p < .05$), and (c) having contraband seized during the course of a stop (189%, increase in odds, $\beta = 1.06$, $p < .001$). Four variables are associated with a decrease in the odds of the driver being a minority member: (a) daytime stops (27%, decrease in odds, $\beta = -.3241$, $p < .001$), (b) officer's level of experience (2.5%, decrease in odds , $\beta = -.0252$, $p < .001$), (c) driving with an out-of-state driver's license (39%, decrease in odds,

Table 4. Logistical Regression Analysis for Correlates Predicting Citations, Arrest, and Search Requests

	Citation			Arrest			Search		
Variable	*B*	*SE*	Exp(*B*)	*B*	*SE*	Exp(*B*)	*B*	*SE*	Exp(*B*)
Minority driver	.282**	.092	1.32	0.727***	.161	2.07	1.37***	.246	3.97
Driver's age	−.015***	.002	0.985	−0.01*	.005	0.989	−0.034**	.021	0.966
Male driver	−.005	.063	1.00	0.824***	.167	2.82	1.53***	.377	4.64
Out-of-state driver's license	.024	.077	1.02	−0.046	.178	1.04	0.287	.338	1.33
In-state registration	.759***	.135	2.13	0.570	.323	1.76	−1.3***	.375	0.267
Equipment	.038	.109	1.03	−1.0***	.240	0.352	−.07***	.404	0.932
Moving	.622***	.108	1.86	−0.724**	.233	0.484	−0.25***	.400	0.774
Seizure	.316	.317	1.37	3.75***	.334	42.8	3.8***	.364	48.3
Black officer	−.355	.227	0.700	−0.966	.779	0.380	0.327	.676	1.38
Male officer	.718***	.145	2.05	−0.139	.258	0.870	−1.1***	.388	0.323
Working days	1.18***	.070	3.26	−1.1***	.162	0.347	−1.5***	.301	0.205
Years of service	.069***	.004	1.07	−0.04***	.010	0.958	−0.027	.017	1.02
Constant	−3.18***	.247		−2.1***	.504		−2.43**	.795	
Model χ^2	1,138.4***			332.0***			260.2***		
Nagelkerke R^2	.254			0.188			0.309		

Note: $N = 5{,}417$. 1 = *yes*; 0 = *no*.
*$p < .05$. **$p < .01$. ***$p < .001$.

$\beta = -.4920$, $p < .01$), and (d) driving a car with an in-state registration (61%, decrease in odds, $\beta = -.9524$, $p < .001$).

Table 4 shows logistic regression results for outcomes of a stop. Results indicate that minority status affects the poststop outcomes of traffic stops in Corner City. For all drivers stopped, net of the other variables in the analysis, the odds were greater that minority drivers were (a) issued tickets (1.32 times greater, $\beta = .282$, $p < .01$), (b) arrested (2.07 times greater, $\beta = .727$, $p < .001$), and (c) searched (3.97 times greater, $\beta = 1.37$, $p < .001$). In terms of the control variables, for each outcome, younger drivers who were stopped for moving violations were more likely to be sanctioned than others. More experienced male officers who worked days were more likely to issue tickets than others, but younger officers working at night were more likely to make an arrest during a traffic stop. A seizure was much more likely if an arrest or search was conducted than if it was not. Drivers occupying vehicles with in-state registrations were more likely to be issued a citation, but drivers who were asked to be searched tended to occupy vehicles without state plates.

The findings from logistic regression analyses are consistent with disproportionate enforcement. In Corner City, for all drivers who were stopped by the police, minority members were more likely to be issued a citation, arrested, and requested to be searched than others.

Although logistic regression is useful in identifying disproportionality at the level of an organization, it cannot be used to identify individual disproportionate conduct. So although the method can be used to investigate whether a police department as a whole is disproportionately stopping minority drivers, it cannot identify which specific members of the department are responsible for the findings. Moreover, the bases for the current findings are open to interpretation. As in nearly any social-scientific multivariate investigation, the independent and control variables used in these analyses do not account for all the variation observed in the outcome variables. Consequently, some attempt must be made to explain this remaining variance. Although the findings could be the result of the predictor variables used in the models, it is also possible that they could stem from key pieces of information not included in the analysis. For example, Corner City officers' discretionary behavior may not be solely responsible for the disparity in arrest rates reported in Table 4. Instead, some of the inequity may stem from differences between the races in the proportion of drivers who were arrested for bench warrants or signed criminal complaints. Officers have very little discretion for these types of arrests. This supplementary explanation is a possibility in Corner City because the Uniform Crime Report suggests that minority members disproportionately offend for crimes that take place outside of traffic stop contexts (i.e., 36% of index offences and about 19% of other offences involve minority members). Unfortunately, we are unable to analyze this question because the Corner City traffic stop arrest data does not specify the reason for arrest.

For our purposes then, alternative explanations include things like differences between racial groups in (a) driving behavior, (b) vehicle condition, (c) driver's attitude, and (d) offending rates not related to traffic stops. In what follows, we introduce a statistical algorithm that can be used to address these limitations. This estimator is fundamental in recognizing and classifying individual disproportionate conduct and can be used in tandem with benchmarks and odds ratios to interpret competing explanations stemming from omitted variables. The algorithm extends Tomaskovic-Devey et al. (2004). Their work examined disproportionality in traffic stops; this algorithm can be used to identify disproportionality in the outcome of a stop. As such, it can be used by researchers and police administrators as an early warning device for the detection of potentially improper police conduct

An Abstract Estimator of Behavior

The symbol Θ_{ij} is a statistic used to represent officers' behavior. The subscripts indicate officer *i*'s outcome for behavior *j*. As noted, we are interested in three traffic stop–related events. The subscript *j* is a placeholder for each of these measures. This subscript can represent traffic stops (t), citations (c), and searches (s). For example, Θ_{iT} corresponds to officer *i*'s traffic stop behavior, Θ_{iC} represents *i*'s ticketing behavior, and so on. For any officer, a value of Θ_{ij} greater than a stipulated threshold value (represented as τ) suggests disproportionate activity and warrants further investigation. More succinctly,

$$\text{If } \Theta_{ij} > \tau \text{, then look further for disproportionality.} \quad (1)$$

The traffic stop estimator Θ_{iT} is a disproportionality index (Tillyer, Engel, & Woolrdredge, 2008). It is depicted in Figure 1 and is based on Tomaskovic-Devey et al. (2004).

This index compares the actual and expected stop rates for minority drivers and others. The two poststop outcome estimators Θ_{iC} and Θ_{iS} are disproportionality odds ratios (Tillyer et al., 2008). These measures compare the odds of some event for minorities to the odds of the event for nonminorities. These odds ratios identify how much more likely it is that minority drivers are ticketed or searched in comparison with nonminority drivers.[11] Both the disparity index and ratios can take on any positive value. Values different from 1.0 are indicative of disproportionality. Values larger than one suggest increased disparity against minority drivers (e.g., they are more likely to be ticketed), whereas values less than one imply decreased disparity (e.g., minority drivers are less likely to be ticketed).

For each estimator, the threshold can be set at any level the analyst deems appropriate. The logic of this is similar to statistical reasoning. The analyst should initially assume no disproportionality (a null hypothesis) and then set the threshold to a suitable level. This level is analogous to the alpha level in a statistical analysis. Threshold values distant from 1 are conservative and should be used in contexts where the analyst is interested in guarding against false positives or unwarranted accusations against officers (i.e., Type 1 error). Threshold values closer to 1 should be used in situations where the analyst is interested in guarding against false negatives or the possibility of failing to identifying disproportionate activity (i.e., Type 2 errors).

These measures are used to model four ideal types (Weber, 1968) of disproportionate police behavior. The models are generically labeled as Type 1, Type 2, Type 3, and Type 4 and are depicted as a tree diagram in Figure 2.[12]

$$\Omega_m = \frac{\textit{Percentage of Minority stops}}{\textit{Minority Baseline}}$$

$$\Omega_{w\&a} = \frac{\textit{Percentage of Whites and Asians stops}}{\textit{White and Asian Baseline}}$$

$$\Theta_{iT} = \frac{\Omega_m}{\Omega_{w\&a}}$$

Figure 1. The traffic stop odds ratio

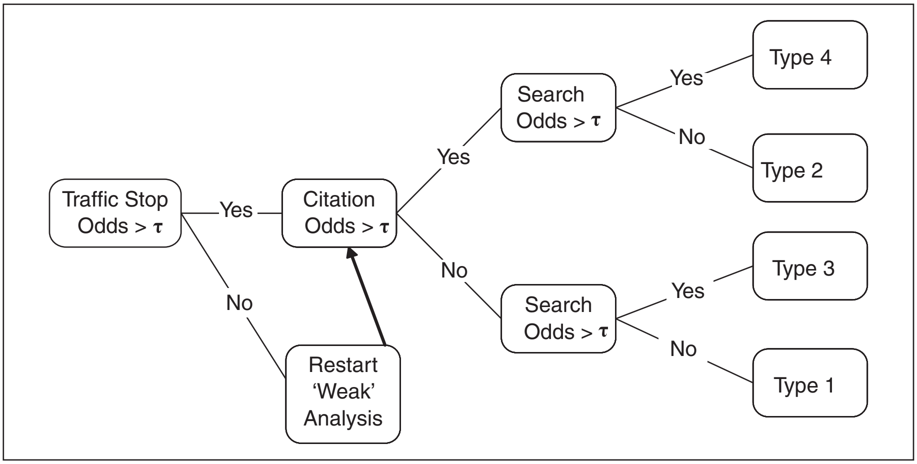

Figure 2. The tree diagram of the models of racially biased policing

Following the paths of the tree diagram leads to a conclusion.[13] By this method, it is clear that Type 1 behavior occurs when an officer stops minorities at disproportionate rates but does not ticket or search them at disproportionate rates. Type 2 behavior occurs when an officer stops and tickets minorities at asymmetrical rates. Type 3 behavior occurs when an officer unequally stops and searches minorities, and Type 4 behavior occurs when an officer stops and tickets and searches minorities at unequal rates. The algorithm always begins with the traffic stops index because officers must first stop a vehicle before they can ticket or request a search of the driver. Consequently, Θ_{iT} is the fundamental index and is a strong indicator of disproportionality.

Although it is impossible to infer an officer's psychological motivation solely from traffic stop behavior, these four types of behavior may serve as a guidepost or tool that may provide some direction or insight in the search for the reasons for officers' behavior. These models then may serve as a rudimentary instrument that can be used to point the way for a researcher to look when searching for motivations of an officer's behavior.

This process will be elaborated later. For now, we will merely mention that Type 1 behavior may suggest stereotyping or unconscious cognitive activity, Type 2 behavior may point toward discrimination, Type 3 behavior toward the use of a profile, and Type 4 may be indicative of a combination of motivations.

The internal benchmark. An internal benchmark compares similarly situated officers. It is used as a tool to evaluate officers side by side to see if they are performing their duties in a like fashion. As such, the measure should consist of suitable items on which officers can be compared. In general, these items include such standards as the time of day worked, the type of assignment (e.g., patrol vs. traffic), the beat the officer is assigned to, the reasons for the stop, and the residence of the driver. The last two items are valuable in assessing whether an officer is using a list of criteria to identify vehicles that are suspicious or should be stopped. Unfortunately, some benchmark measures are not appropriate or available for the Corner City Police data. First, the officers' type of assignment is not suitable for this examination. The department does not have a dedicated traffic division or gang division, and therefore no delineation between patrol and other assignments is possible. Second, although in theory most Corner City officers are assigned to patrol beats for extended periods of time, they are often forced to switch assignments to fill in on beats that are temporarily understaffed because of illness or vacation. In practice then, beat assignments tend to vary day to day. Moreover, during the course of a shift, officers are routinely dispatched to calls off their beats. This means officers spend significant portions of their shifts working outside of their assigned areas. Officers are given freedom to make self-initiated traffic stops while off their beats. As a result, a significant portion of the officers' stops occur outside of their designated areas of patrol. Unfortunately, the Corner City data does not track this information, and so it's impossible to use the data to quantify the proportion of each officer's traffic stops that occur outside their assigned areas. These factors make it impractical to use beat assignments as an internal benchmarking standard.

The analysis. Table 5 below, lists the values of the statistics used in the tree diagram analysis. These measures include the counts and calculated disparity index for stops (Θ_{iT}) and the poststop outcome odds ratios for citations (Θ_{iC}), and search requests (Θ_{iS}). The table also lists several pieces of data to be used for officer-to-officer comparisons. All 41 Corner City units are evaluated in this analysis.

For this analysis, we set the threshold value (τ) for traffic stops equaling 4.0. This value is very conservative and roughly corresponds to two standard deviations above the mean. When threshold values are set this high, only officers exhibiting the most extreme disproportionate traffic stop activity will be identified. Consequently, any index value larger than this threshold strongly suggests disproportionality and indicates that the researcher should continue following the paths through the tree diagram. Setting threshold values this high reduces the plausibility of alternative explanations due to omitted variables because these explanations tend to become less relevant as the magnitude of estimated differences increase (Analysis Group, 2006). Next, we set the threshold values (τ) for the citation and search odds ratios to less conservative values equaling 2.0, respectively. Because the initial layer of the analysis identified officers whose traffic

Table 5. Tree Diagram Analysis and Internal Benchmarking Information

	Internal benchmarks				Algorithm odds ratios, counts, and outcomes						
Unit number[a]	Years service	Percentage equipment violation stops	Percentage out-of-state stops	Time of work	Number of stops	Stop odds	Number of citations	Citation odds	Number of requests	Search odds	Behavior
1	13	19.14	4.96	Day	141	0.837209	50	0.902174	1	—	
2(a)[b]	4	46.05	7.28	Evening	151	2.121951	48	2.922078	0	—	
2(b)[b]	6	46.05	7.28	Evening	151	2.121951	48	2.922078	0	—	
3	5	46.22	7.54	Night	106	1.840909	19	0.522059	5	1.235294	
4	4	21.60	9.87	Evening	162	0.467532	75	2	1	—	
5	1	36.60	6.53	Night	153	1.276119	39	3.12	5	—	
6	2	41.17	13.13	Night	100	1.314607	16	0.974026	6	1.4	
7	12	38.57	5.71	Night	280	1.08	171	0.602564	0	—	
8(a)[b]	7	72.88	3.95	Night	177	4.057377	29	3.439842	16	3.214286	Type 4
8(b)[b]	30	72.88	3.95	Night	177	4.057377	29	3.439842	16	3.214286	Type 4
9	8	67.16	5.97	Day	67	1.578947	32	1.788462	0	—	
10	1	45.45	4.47	Evening	67	1.396552	12	0.534091	0	—	
11	7	33.33	1.19	Evening	147	2.211864	33	1.417143	20	—	
12	7	50	22.72	Evening	22	0.9	5	4	0	—	
13	3	61.11	5.55	Evening	90	3.089552	7	9.027778	0	—	
14	24	29.21	4.07	Day	881	0.574699	655	1.752319	0	—	
15(a)[b]	1	36.53	8.85	Night	270	0.602362	59	4.59	8	10.67143	
15(b)[b]	13	36.53	8.85	Night	270	0.602362	59	4.59	8	10.67143	
16	6	46.26	5.97	Evening	67	1.220339	37	0.787879	0	—	
17	16	17.42	3.78	Day	132	0.983193	98	2.022989	1	—	
18	8	33.96	2.51	Evening	159	1.759398	58	4.238482	1	—	
19	23	25	5.00	Day	20	1	0	1	0	—	
20	1	34.93	4.81	Evening	83	1.671429	46	1.347368	0	—	
21	22	17.09	62.93	Evening	117	5.04	17	1.3	30	3.243077	Type 3
22	5	62	0.08	Night	99	0.677419	28	7.608696	0	—	
23	2	38.13	9.32	Night	117	1.411765	21	1.076923	0	—	

(continued)

Table 5. (continued)

	Internal benchmarks				Algorithm odds ratios, counts, and outcomes						
Unit number[a]	Years service	Percentage equipment violation stops	Percentage out-of-state stops	Time of work	Number of stops	Stop odds	Number of citations	Citation odds	Number of requests	Search odds	Behavior
24	20	27.58	6.40	Day	203	0.369231	77	0.981081	0	—	
25	20	28.73	2.29	Day	87	0.54878	57	2.188679	0	—	
26	20	41.48	2.12	Night	94	1.071429	71	0.438462	1	—	
27	19	42.59	7.81	Day	486	0.467532	355	0.242236	0	—	
28	19	53.84	23.07	Day	26	1.636364	5	0.00085	0	—	
29	13	15.95	14.89	Evening	92	1.192771	39	1.818182	3	—	
30	19	5	2.50	Day	40	1.588235	31	0.518519	0	—	
31	>1	51.28	7.69	Evening	39	1.636364	6	10	0	—	
32	3	46.15	12.30	Night	65	1.636364	13	3.407407	5	4.333333	
33	2	82.14	1.19	Evening	168	4.147826	42	2.235294	6	4.612245	Type 2
34	17	13.33	10.55	Day	179	0.585799	80	0.448052	0	—	
35	6	40.78	5.26	Evening	76	1.058824	2	0.004125	0	—	
36	13	21.95	9.75	Night	41	2.903226	9	1.785714	0	—	
37	9	21.21	6.25	Night	33	1.607143	6	1.15	0	—	
38	8	33.87	20.96	Evening	63	0.62069	14	1.153846	0	—	
39	8	15.38	10.25	Day	39	2.322581	11	3.428571	0	—	
40	7	42.47	0.885	Evening	113	0.873786	42	8.117647	0	—	
41	8	36.84	0	Evening	38	0.771429	5	0.002	0	—	

a. These numbers are fictitious.

b. Indicates officers who permanently ride together as partners in the same car. These officers' cars are given the same numerals but are differentiated with the letters "a" and "b" within parentheses.

stop behavior was very disproportionate, we elected to use this less conservative value to closely examine the outcomes of their stops. This methodology guarded against false negatives, including the possibility of failing to identify disproportionality in officers whose behavior is already suspect.

Outcomes for police units are given in Table 5. A *police unit* is defined as either a one or two person car. In Corner City, there are three fixed two person cars. The officers who are assigned to each of these cars generate identical traffic stop statistics and are treated as a single unit for the analysis.

We first briefly summarize the results in Table 5 and then use the results to discuss whether this information indicates some Corner City officers are treating minorities unfairly. The first layer of analysis compares each officer's disparity indices and ratios to preset threshold values. If disparity is suggested, the identified officer is then directly compared to other similarly situated officers using internal baseline information, including years of service, shift assignment, and reason for stop.

Summary of outcomes. Every unit working in Corner City during 2007 was analyzed. The number of stops, citations, and searches varies from unit to unit. A goal of this analysis is to spot patterns in the data, which are then used to make comparisons between units.

Interpretation. Results of the analysis in Table 5 suggest that three units' traffic behavior was disproportionate and warrants further attention.[14] However, a finding of disproportionality does not automatically indicate unfair treatment because the outcome may be the result of alternative explanations. For these data, however, three competing explanations are implausible. The first concerns the (a) differences between the races in driving quantity or mobility. This study uses a highly reliable observational method to establish baseline percentages of racial groups on the roads of Corner City at virtually all times of the day and night. (b) The second concerns the directed patrol. An examination of 2000 U.S. census data by block groups reveals that minority members' residences are more or less evenly distributed throughout the community. The observational baseline data suggests there are no temporal variances in minority driving patterns, and an examination of Corner City staffing shows that no officers are assigned to special units, such as gang investigation, drug interdiction, or vice. Consequently, there are no known geographic, temporal, or organizational patrol directives that are likely to increase the odds that certain officers encounter higher percentages of minorities than others. Therefore, directed patrol cannot account for disproportionality.[15] (c) The third concerns the differences between the races in driver quality. Logistic regression analysis found that minorities were no more likely to be stopped for moving violations than other drivers.[16] This implies that driving quality does not vary between the races.

In what follows, we demonstrate how the results can be used to inspect the conduct of identified units. For the sake of brevity, we examine only one of the three identified units—Unit 21. We first give a brief description of the unit's activity, then a juxtaposition of competing explanations, and finally a short comment about the plausibility of explanations. These comments are not meant so much as definitive conclusions as they are examples that illustrate how the internal benchmark and other data sources can be used to assess the reasonableness of the hypotheses against competing explanations.

Described below is an example analysis. Several steps should be followed when examining claims of disproportionality. These include the following:

- summarizing the disproportionate activity,
- identifying explanations based on disproportionality,
- identifying alternative explanations,
- comparing the disproportionate unit to other similarly situated units,
- evaluating the plausibility of the competing explanations.

Description of activity. Unit 21 is a White officer whose traffic stop activity was very disproportionate. For all cars stopped by this unit, the odds were more than five times greater that the driver would be a minority than a nonminority. Unit 21 differs from other Corner City units in two other important respects. First, this unit stopped cars without of state license plates much more frequently than other units did. Sixty-two percent of cars stopped by Unit 21 had out-of-state plates. The average for the department was just 9%. Second, Unit 21 made many more minority search requests than any other unit. Unit 21 made 30 search requests. The average for the department was less than 3. In addition, for all vehicles stopped by this officer, Unit 21 was three times more likely to search minority-driven vehicles than nonminority cars.

A provisional conclusion based on inequitable treatment of minority drivers. Unit 21 treated minorities unfairly by using minority status in tandem with out-of-state residency as criteria (perhaps as a profile) to identify drivers who need to be stopped and searched.

A provisional conclusion based on an alternative explanation. Unit 21's conduct was reasonable. The conclusion is based on the following premises: (a) by chance or organizational practices, Unit 21 stopped a comparatively high percentage of out-of-state cars driven by minority members. (b) Once stopped, minority drivers' behavior or attitude suggested that a search was warranted.

The Plausibility of Premises

Premise (a). By chance or organizational practices, Unit 21 stopped a high percentage of out-of-state cars.

Corroborative information: The results from logistic regression indicate that once a stop had taken place, driving a car without of state plates was associated with an increase in the odds that the driver was a minority.

Noncorroborative information: Officer-to-officer comparisons show that no other unit stopped as high of percentage of out-of-state vehicles as Unit 21 did. In fact, the nearest unit was nearly 40 percentage points below (23.07%). The average for the department was just 8.4%. Moreover, as previously noted, the disproportionality is not likely due to structural factors like differences between the races in driving patterns or organizational practices such as directed patrol.

Premise (b). Minority drivers' behavior or attitudes generated searches.

Corroborative information: no information available.

Noncorroborative information: Officer-to-officer comparisons show that Unit 21 made many more minority search requests than any other unit. In fact, the vast majority of other units made zero or only one request. For this premise to be true, one would need to believe that no other Corner City unit encountered (or cared about) minority drivers with a provocative attitude or posture.

A Conclusion Based on This Evidence. The evidence suggests the following: first, that Premise (a) is probably not true. It is doubtful that chance alone generated the disproportionality found in Unit 21's traffic stop behavior of out-of-state cars. Second, Premise (b) is likely false. It seems unlikely that the attitudes of minority provoked suspicion warranting a search. Officer-to-officer comparisons indicate that no other similarly situated units stopped and searched minority drivers at similar rates. Observational and internal baseline data also suggest that Unit 21's disparity was not likely due to social structural factors, such as disproportionate crime rates among minority members, patrol assignments, the officer's level of experience, or temporal factors like time of day. Overall, the sum of the evidence suggests that the disproportionality in Unit 21's stops and search requests is probably not justified.

A Step Toward Linking These Behaviors With Motivation

Once unfair treatment of minority drivers has been found, the next step is to try and understand the officer's motivation for the disproportionality. The realization of this task, however, has proven to be challenging in part because it is impossible to know for certain what is going on inside an officer's mind at the time of a traffic stop. So, although statistical analysis is useful in identifying disparity, its reliability for determining motive is questionable (Tillyer et al., 2008). Despite this, the outcome models generated by the algorithm, when considered in concert with officer-to-officer comparisons, may serve as a guidepost or instrument that may provide some guidance or insight that can be used in attributing motivations for the officers' behavior. These models then may serve as a rudimentary tool that can be used to point the way for a researcher to look when analyzing an officer's behavior. The discussion that follows is preliminary. The description of the models is a first step along the road linking officers' behavior with motivations. This association should be corroborated with other empirical evidence before the conclusions coming from this methodology can be considered definitive. As noted, four types of motivational processes are likely to be present in any context where the police make race-sensitive choices. Next, we preliminarily describe how the abstract models generated by the algorithm may be indicative of three of these processes. For reasons discussed above, directed patrol should not be used to explain officers' conduct for this data set.

Racial Profiling refers to the use of race as one of a set of identifiers employed in determining the suspiciousness of a person. A profile involves the strategic use of race in decision making. Officers employing this tactic use race as a kind of shorthand to identify potential criminals for stops, searches, and arrests (Harris, 2002). For a street officer, the goal of profiling is often interdiction of drugs or weapons. This process consists of two elements: a stop and a search. Accordingly, disproportionality in traffic stops and searches, especially in isolation of other types of disparity, may be an expression of this conduct. In circumstances where this is true, behavior classified as Type 3 in the algorithm is emblematic of profiling. Therefore, when Type 3 behaviors are found during an evaluation, the analyst should look for other identifiers that may suggest the officer is using race strategically as a proxy for criminal behavior. These identifiers include disproportionality in a list of violations that could be used as a pretext for stops (e.g., equipment violations or subjective charges such as weaving), criteria that could be used to infer criminality (e.g., a combination of race and out-of-state residency), or disproportionate behavior among officers assigned to special enforcement teams. Research suggests that Type 3 disproportionality in stops and searches from members of these types of units is consistent with profiling (Smith & Alpert, 2007; Smith et al., 2003). Widespread Type 3 disproportionality among officers working these details may indicate organizational (social structural) forms of racial profiling, whereas more isolated disparity among officers may be indicative of individual profiling (human agency).

Discrimination is negative behavior directed at others based on an active dislike stemming from their membership in a minority group. In a police setting, this type of behavior may materialize as highly discretionary conduct that results in the unjustified stopping of minority drivers to unfairly penalize them in some way. Issuing a citation is a good indicator of this type of activity because, generally, officers have a great deal of freedom in choosing whether to issue tickets for minor infractions. In principle, then, disproportionate traffic stop activity and highly discretionary disproportionate sanctioning activity may be indicators of discrimination. In contexts where this is true, behavior classified as Type 2 in the algorithm suggests discrimination. Although there are many plausible reasons why an officer may disproportionately stop and ticket minority drivers, analysts who find Type 2 behaviors should be diligent in attempting to discover whether the identified officers are basing their actions on antipathy for minority group members. Due diligence includes psychometric evaluations, appraising alternative explanations in light of internal benchmark data, and assessing the degree of disproportionality, guided by the assumption that ceteris paribus an attribution of prejudice or discrimination becomes more reasonable as the degree of disproportionality increases.

Stereotyping is the product of unconscious cognitive activity that leads to oversimplified beliefs, which are used to cognitively organize the social world. Stereotypes become manifest as a gut feeling that officers use to infer increased criminality of minorities. These thoughts and feelings are often the product of illusionary correlation mechanisms that develop from socialization and repetitive memories of negative behaviors that co-occur with minority contact. In a traffic context, such an outlook may lead to stopping minorities at disproportionate rates. However, a gut feeling is nonvolitional. It is neither the product of racial animus nor the result of the strategic use of race as a marker for criminality. So, in isolation of other factors, officers whose decisions are impacted by implicit stereotyping are less likely to sanction or search minority drivers than prejudiced or officers who are profiling are. It follows then that unconscious cognitive stereotyping may materialize in police work as disproportionate traffic stop activity in the absence of any other type of disproportionate activities. In circumstances where this is true, this behavior pattern may correspond to Type 1 conduct.[17] Recent theory suggests that this type of police conduct is common in contexts where norms are ambiguous and officers are tired, distracted, or forced to make snap judgments (Gilbert & Hixon, 1991; Smith & Alpert, 2007). Although common, we argue this is a subtle process that generates less extreme forms of disparity than open discrimination or explicit profiling. So, paradoxically, when algorithm threshold values are set high, this type of activity is less likely to be detected, even though it widely affects behavior.

Combination is a residual category that is used to classify behavior that cannot be set apart as a separate concept. In set theory, it would be defined as the union of discrimination and profiling. It is behavior consisting of three types of disproportionate activity: traffic stop, ticketing, and searching. This combination of motives corresponds to Type 4 behaviors and is not of immediate theoretical interest.

Conclusion

Research consistently demonstrates that minority group members evaluate the police more negatively than other people do. These feelings may stem from various forms of police conduct that lead to disproportionality in traffic stops, searches, and arrests. The roots of these practices are embedded in social psychological and social structural processes. This study examines the link between these processes and police behavior by analyzing the traffic stop data of a medium-sized police department we call the Corner City P. D. The investigation had three principal goals: first, to determine if the Corner City police were disproportionately stopping and sanctioning minorities; second, if so, to generate an algorithm that can identify individual officers who were acting this way; and third, to generate theoretical models that can specify why. The algorithm can be used by police administrators as an early warning device in identifying officers whose traffic stop activity may be inequitable. If unfair treatment of minority drivers is found, an analyst can use the models as a rudimentary instrument that may be useful in understanding the officer's disproportionality. It is well understood that one of four cognitive or structural processes is likely to be present in contexts where the police make race-sensitive choices. The abstract models are a tool that can be used to point toward these potential sources of disproportionality.

Unlike most previous studies, this investigation examines disproportionate activity along two broad dimensions. A macrolevel investigation examines the behavior of the Corner City Police Department as an organization. Results from logistic regression suggest that on average Corner City officers disproportionately stop, ticket, and search minority drivers. A second microanalysis explores the behavior of individual officers. This information is used to specify four abstract models of disproportionate police conduct. Results suggest that three Corner City officers' behavior was disproportionate. The algorithm and models used in this analysis may serve as an elementary starting point in linking observable disparity to the sources of disproportionality often specified in this literature, including discrimination, unconscious stereotyping, racial profiling, and directed patrol. For this data set, our analysis suggests that officers' conduct could not be due to directed patrol.

The baselines for this analysis were developed in and applied to a small city with a predominately uniform race representation. This reduced the complexity in establishing a valid baseline. Nearly all areas of Corner City are similar in racial composition. Consequently, it was a comparatively straightforward task for field observers to gather suitable data for demographic summaries of drivers in the city. A valid baseline eliminates several alternative explanations for officers' behavior, including differences between the races in driving quality, quality, or mobility.

Researchers examining more heterogeneous communities may be able to use this method by focusing on smaller sections of municipalities, such as a district, precinct area, or a police beat. Often these divisions are very uniform in terms of race and other socioeconomic status factors. In situations where this is the case, an algorithm and models can be developed for these smaller sections. Practitioners, who examine officers' conduct in larger departments then, may want to reduce the focus of analysis from an entire department to, for example, a precinct, a shift, or a sector of town. In practice, these tools may ultimately interest police managers more than researchers because their microscope may potentially enable police supervisors to take corrective action against individual officers before serious ramifications, such as citizen complaints and lawsuits, occur.

A limitation of this study is that the data set used made it difficult to examine the influence of the drivers' behavioral cues on formulating suspicion. The issue of drivers' reactions and behavior is important given the mistrust of the police among minorities. Several researchers have noted the importance of considering behavioral cues such as hostility or indifference on officer behavior (e.g., Alpert, MacDonald, & Dunham, 2005; Johnson, 2006; Smith et al., 2006). Even so, it seems improbable that minority-driver behavioral cues were responsible for most of our findings. First, the initial layer of the algorithm detects disparity in traffic stops, not outcomes. If there is no disproportionality in traffic stops, then the algorithm will not find disparity in outcomes. Second, the targets' demeanor generally affects officers' decisions related to stop outcomes more than traffic stops. That is, a suspect's hostility is more likely to color an officer's decision to ticket the driver than to initially stop the vehicle. This follows because an officer's decision to stop a vehicle generally comes before any assessment of the target driver's behavioral cues can be made. The fluid nature of patrol makes it difficult for officers to observe drivers' behavioral cues prior to a stop. Most of the time, the officer simply does not have the means to form judgments about the unfriendliness of the driver before the stop. Therefore, traffic stop disproportionality identified by the algorithm is probably not significantly influenced by the target's behavioral cues. As noted, however, suspect demeanor can play a role in affecting disproportionality in stop outcomes. Consequently, researchers using the algorithm should interpret their findings in light of internal benchmark information (e.g., are all similarly situated officers behaving this way?) and algorithm threshold values. The higher these values, the more extreme the disparity and the less likely it stems solely from reactions to suspects' demeanor.

Work yet to be done includes developing a more focused and nuanced understanding of internal baseline data. The analysis found three disproportionate units working in Corner City. These units were similar in some respects but different in others. For instance, all units operated during the evening and night shifts, but each varied considerably in years of experience. This begs the question: Is there something about working night and evening hours that is relevant? The information from the observational baseline suggests not. It confirms that there was no significant difference in percentages of minority drivers on the roads between daytime and nighttime hours or weekdays and weekends. Information from the internal baseline supports this. If working evening hours is relevant, why are only three units working these hours disproportionately stopping minority drivers? Differences between shifts in level of experience do not seem to matter either. Although, on average, day-shift officers are more experienced than other shifts, one of the identified units was the most experienced on the department, whereas another was nearly the least experienced. Future elaborations must focus on developing methods for efficiently analyzing increased sources of information, including differential offending rates, the suspect's demeanor, the suspect's vehicle condition, the possible effects of bystanders or passengers, and the effects of working different shifts (e.g., the reduced visibility in identifying races at night).

In summary, by providing well-defined differences in meaning between the terms, and by providing a firm statistical underpinning for each, this analysis develops an algorithm and models of behavior that can be used to identify inequitable police conduct and serve as a rudimentary guide or tool that potentially may be used to point toward sources of the disparity.

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Notes

1. As an example, consider psychological research investigating implicit cognitive thinking. This work has demonstrated that at times racially biased police conduct coexists with fair minded intentions (Payne, 2006). Officers making snap judgments can act in a biased fashion toward minorities without a conscious intention to do so. However, because of the present confusion over the meanings of terms in the profiling literature, it is quite possible that this

type of unintended racially biased policing could be lumped together with more pernicious forms of police behavior based on deliberate racial hostility and animus. This ambiguity is vexing because isolating the sources of police disproportionate behavior likely has important implications for both theory and policy.

2. Part of our analysis of racial disparity is conducted at individual officer level. The pseudonym for the department is used to protect the identities of these officers.
3. We wish to thank an anonymous reviewer for suggesting this observation.
4. Some of this data has been statistically analyzed by researchers. However, a comprehensive review of this literature has been done elsewhere and is beyond the scope of this article. See, for example, Batton and Kadleck (2004); Engel, Calnon, and Bernard (2002); or Alpert, Dunham, and Smith (2007) for a comprehensive review.
5. If the officer's thoughts and feelings are based on actual experiences (rather than illusionary correlations) that are supported by local crime rates and calls for service information, then the officer's behavior is not stereotyping. Instead, it closely resembles our definition of profiling (see next section). At some conscious cognitive level, the officer's experience suggests that race can be used to identify criminality. Consequently, the officer is using race as a criterion in determining the suspiciousness of a person.
6. As an anonymous reviewer noted, at times the use of profiles may be understandable or even justifiable. For example, if officers make decisions based on actual experiences that are supported by knowledge of local crime rate and calls for service, then the officers' actions may be reasonable.
7. Officers in Corner City work three shifts: days, evening, and nights. For logistic regression, these shifts were collapsed into two categories: stops that occurred during the daytime hours and stops that occurred at night.
8. Following Novak (2004), Asians are included with Whites in the majority category because racial profiling that invoke stereotypical assumptions about dangerous classes of people revolves primarily around Blacks, Latinos, and other non-Whites (Shelden, 2001). However, analyses were also conducted on a data set where Asians were not included in the majority category. We found no substantive differences in results, which are available from the lead author on request.
9. The nonparametric chi-square estimate for differences between the observation and census percentages is significant ($p < .01$); however, the result should be discounted because the likelihood of a nonmeaningful significant finding is considerably inflated due to the large sample size.
10. The results in Table 4 were reanalyzed two more times: (a) without seizure included as a variable and (b) without officers' race included as a variable. In both instances, there were no substantive changes in the results. That is, in either case no remaining variables changed levels of significance. These results are available from the lead author on request.
11. The calculation of the odds ratio for citations and search requests is a comparison of the odds of some event for minorities to the odds of the event for nonminorities. For example, the following is used to calculate the odds ratio for citations for a given officer:

PM = Number of stops involving minority drivers where a citation was issued,
QM = Number of stops involving minority drivers where a citation was not issued,

PW = Number of stops involving nonminority drivers where a citation was issued,
QW = Number of stops involving nonminority drivers where a citation was not issued,
Θ_{iC} = (PM/QM) ÷ (PW/QW).

12. The variable arrest was not included in the tree diagram for two reasons: First, it contains somewhat redundant information in terms of punitive action with the citation variable. Second, tree diagrams become unwieldy and difficult to interpret as variables are added. Therefore, we elected to include only the citation variable, which has a much larger number of cases.
13. Citations and searches are independent events. One is not predicated on the other. For example, often the decision to issue a citation can occur prior to a decision to search (even though the actual issuing of the ticket occurs after the search). Moreover, citations are much more frequently occurring events than are searches. Therefore, we decided to place citations prior to searches in the tree diagram.
14. Logistic regression results suggest that disproportionality also exists at the level of the organization. Are these three officers primarily responsible for this finding? To investigate this question, we conducted another logistic regression for the correlates of predicting driver's race once a stop has occurred without these three identified units included. There were no substantive differences in results. The overall level of disproportionality remained (results available from the lead author on request). These findings suggest that the identified officers do not solely account for the disproportionality found at the level of an organization and that these three officers' behavior is not offset by other Corner City officers who rarely stop minority drivers.
15. For these same reasons, it also seems unlikely that officers would perceive minority members as more out of place (Novak & Chamlis, in press) on some beats than others.
16. Due to space limitations, this analysis was not included in Table 4. Results are available from the lead author on request.
17. Strictly speaking, stereotyping is a subset of discrimination and a subset of profiling and so occurs concurrently with discrimination and profiling. However, we feel it is theoretically useful to conceptualize these as separate processes.

References

Alpert, G. P., MacDonald, J. M., & Dunham, R. G. (2005). Police suspicion and discretionary decision making during citizen stops. *Criminology, 43*, 407-434.

Alpert, G. P., Dunham, R. G., & Smith, M. R. (2007). Investigating racial profiling by the Miami-Dade Police Department: A multimethod approach. *Criminology & Public Policy, 6*, 25-56.

Alpert, G. P., Smith, M. R., & Dunham, R. G. (2004). Toward a better benchmark: Assessing the utility of not-at-fault traffic crash data in racial profiling research. *Justice Policy and Research, 6*(1), 43-69. Available from www.csa.com

Analysis Group Inc. (2006). *Pedestrian and Motor Vehicle Post-Stop Data Analysis Report: Prepared for the City of Los Angeles*. Retrieved from www.lacity.org/LAPDstops/

Bargh, J. A., & Chartrand, T. L. (1999). The unbearable automaticity of being. *American Psychologist, 54*, 462-479.

Batton, C., & Kadleck, C. (2004). Theoretical and methodological issues in racial profiling research. *Police Quarterly, 7*(1), 30-64. Available from www.csa.com

Devine, P. G. (1989). Stereotypes and prejudice: Their automatic and controlled components. *Journal of Personality and Social Psychology, 56*, 5-18.

DiLulio, J. J., Jr. (1996). My Black crime problem, and ours. Retrieved July 18, 2008, from City Journal Web site: http://www.city-journal.org/html/6_2_my_black.html

Drummond, T. (1999, June 14). It's not just in New Jersey. *Time*. Retrieved February 27, 2010, from http://www.time.com/time/magazine/article/0,9171,991207,00.html

Engel, R. S., Calnon, J. M., & Bernard, T. J. (2002). Theory and racial profiling: Shortcomings and future directions in research. *Justice Quarterly, 19*, pp. 249-273.

Gilbert, D. T., & Hixon, J. G. (1991). The trouble of thinking: Activation and application of stereotypic beliefs. *Journal of Personality and Social Psychology, 60*, 509-570.

Harris, D. A. (2002). *Profiles in injustice*. New York: New Press.

Huesmann, L. R. (1998). The role of social information processing and cognitive schema in the acquisition and maintenance of habitual aggressive behavior. In R. Geen & E. Donnerstein (Eds.), *Human aggression: Theories, research and implications for social policy* (pp. 73-109). San Diego, CA: Academic Press.

Hurst, Y. G., Frank, J., & Browning, S. L. (2000). The attitudes of juveniles toward the police: A comparison of Black and White youth. *Policing an International Journal of Police Strategies and Management, 23*(1), 37-53. Available from www.csa.com

Johnson, R. R. (2006). Confounding influences on police detection of suspiciousness. *Journal of Criminal Justice, 34*, 432-442.

Kennedy, R. (1997). *Race, crime, and the law* (1st ed.). New York: Pantheon Books.

Lamberth, J. (2006). *Data collection and benchmarking of the bias policing project*. Retrieved February 27, 2010, from http://www.workplacebullying.org/docs/lamberth2006.pdf

Macrae, C. N., & Bodenhausen, G. V. (2001).Social cognition: Categorical person perception. *British Journal of Psychology, 92*(1), 239. Retrieved July 23, 2008, from Academic Search Premier database.

Mastrofski, S. D., Worden, R. E., & Snipes, J. B. (1995). Law enforcement in a time of community policing. *Criminology, 33*, 539-563. Available from www.csa.com

Myers, D. G. (2008). *Social psychology* (9th ed.). New York: McGraw-Hill.

Nelson, T. D. (2006). *The psychology of prejudice* (2nd ed.). Boston, MA: Pearson Publishing.

Novak, K. J. (2004). Disparity and racial profiling in traffic enforcement. *Police Quarterly, 7*(1), 65-96.

Payne, B. K. (2001). Prejudice and perception: The role of automatic and controlled processes in misperceiving a weapon. *Journal of Personality and Social Psychology, 81*, 181-192.

Payne, B. K. (2006). Weapon bias: Split-second decisions and unintended stereotyping. *Current Directions in Psychological Science, 15*, 287-291.

Riksheim, E. C., & Chermak, S. M. (1993). Causes of police behavior revisited. *Journal of Criminal Justice, 21*, 353-382. Available from www.csa.com

Shelden, R. G. (2001). *Controlling the dangerous classes: A critical introduction to the history of criminal justice*. Boston: Allyn & Bacon.

Sherman, L. W. (1980). The effects of police reform on political culture: Three case studies. In David M. Peterson (Ed.), *The police: Strategies and outcomes in law enforcement* (pp. 37-57). Beverly Hills, CA: SAGE.

Smith, M. R., & Alpert, G. (2007). Explaining police bias: A theory of social conditioning and illusionary correlation. *Criminal Justice and Behavior, 34*, 1262-1283.

Smith, M. R., Markarios, M., & Alpert, G. (2006). Differential suspicion: Theory specification and gender effects in the traffic stop context. *Justice Quarterly, 23*, 271-295.

Smith, W. R., Tomaskovic-Devey, D., Zingraff, M. T., Mason, H. M., Warren, P. Y., & Wright, C. P. (2003). *The North Carolina traffic study.* Raleigh: North Carolina State University.

State of New Jersey v. Pedro Soto et al., Superior Court of New Jersey,734 A.2d 350, 1996. A Resource Guide on Racial Profiling Data Collection Systems–184768.pdf

Tillyer, R., Engel, R. S., & Wooldredge, J. (2008). The intersection of racial profiling research and the law. *Journal of Criminal Justice, 36*, 138-153.

Tomaskovic-Devey, D., Mason, M., & Zingraff, M. (2004). Looking for the driving while Black phenomena: Conceptualizing racial bias processes and their associated distributions. *Police Quarterly, 7*, 3-29.

Weber, M. (1921/1968). *Max Weber on law in economy and society* (M. Rheinstein, Ed.; E. Shils & M. Rheinstein, Trans.). New York: Simon & Schuster.

Weitzer, R., & Tuch, S. A. (2005). Determinants of public satisfaction with the police. *Police Quarterly, 8*, 279-297.

Wilbanks, W. (1987). *The myth of a racist criminal justice system*. Monterey, CA: Brooks/Cole. Available from www.csa.com

Wilkins v. Maryland State Police, Civil Action No. CCB–93–483, Maryland Federal District Court (1993). Driving while Black: A statistician proves that prejudice still rules the road. *The Washington Post*, p. C1.

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